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Machine Learning-Based Impact Assessment of ERP System Implementation in Business Process Re-engineering

W.G.A. Dushan Sasmitha

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Thesis submitted in partial fulfillment of the requirements for the degree
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DECLARATION

I declare that this is my own work and this thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

Signature:

Date: 01.06.2025

The above candidate has carried out research for the Masters thesis under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of the supervisor: Eng. Prof. Indika Perera

Signature of the supervisor:

Date: 09.06.2025

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I hope the research and conclusions presented herein will provide meaningful insights to readers.

ABSTRACT

Purpose - The purpose of this study is to predict the impact of Enterprise Resource Planning (ERP) implementation on Business Process Reengineering (BPR) in Sri Lankan organizations using machine learning algorithms. By applying the CRISP-DM framework, the research aims to develop and evaluate a predictive model that identifies patterns and relationships between ERP implementation and business process changes, providing actionable knowledge for improving organizational processes.

Methodology - The study will apply the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, integrating data collection, preprocessing, model development, and evaluation to effectively structure and analyze the impact of ERP implementation on BPR in Sri Lankan organizations. Machine learning algorithms will be employed to develop a predictive model, which will be refined and assessed for accuracy and reliability to achieve the research objectives.

Findings - This study analyzes the impact of ERP implementation on BPR in Sri Lankan organizations using the developed model and multiple machine learning techniques. The results indicate that machine learning techniques can effectively predict ERP implementation outcomes, with varying accuracy depending on the algorithm used. Notably, Naive Bayes and Decision Tree models demonstrated high classification accuracy, particularly for responses indicating strong agreement on ERP's impact on BPR. The Gradient Boosting Machines (GBM) model further reinforced these findings, exhibiting exceptional predictive capability, as evidenced by its near-perfect R-squared value.

These findings suggest that ERP implementation significantly influences process transformation by streamlining operations, enhancing efficiency, and achieving reengineering goals. The strong predictive performance of GBM confirms the reliability of these assessments, making it a valuable tool for evaluating ERP impact on business processes.

Potential Implications - This study will facilitate informed decision-making and strategic planning regarding ERP implementation and BPR, thereby enriching the body of knowledge in this field. The findings will serve as a valuable resource for practitioners, managers, and researchers in enhancing ERP implementations and driving successful business process transformations.

Keywords: Machine Learning Algorithms, ERP, BPR, ERP Implementation, Sri Lankan Organizations

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LIST OF ABBREVIATIONS

Abbreviation	Description
ERP	Enterprise Resource Planning
BPR	Business Process Reengineering
CRISP-DM	Cross-Industry Standard Process for Data Mining
ANN	Artificial Neural network
KNN	K-Nearest Neighbor

CHAPTER 1

INTRODUCTION

In today's dynamic business environment, companies face the challenge of anticipating, responding to, and adapting to the ever-growing demands of the marketplace. In this fiercely competitive landscape, a well-executed business strategy not only drives success but also ensures long-term survival. At the core of many modern business strategies is the effective and efficient use of information technology, especially ERP systems.

An ERP system is a comprehensive software solution that integrates and automates a company's processes, including materials management, human resources, and finance. It provides a unified, competency-centered tool for managing organizational resources effectively. Leading ERP vendors, such as SAP, IFS, and Infor, have been widely adopted across various industries like agriculture, engineering, textiles, and electronics. In Sri Lanka, large companies such as Brandix Apparel Limited and Maga Engineering (Pvt) Ltd use Infor, while Singer Sri Lanka uses IFS. Additionally, companies like Vallibel One PLC, LAUGFS Holdings Limited, and Diesel & Motor Engineering PLC rely on SAP solutions.

ERP systems provide businesses with a process-oriented view and offer significant advantages, such as:

- Automating and integrating business processes,
- Sharing common data and best practices across the entire enterprise,
- Enabling real-time information access for informed decision-making.

In this context, Business Process Reengineering (BPR) methodologies have played a pivotal role in transforming organizational processes by focusing on efficiency and innovation. As organizations execute these processes, large volumes of data are generated. This is where machine learning algorithms become essential, as they enable organizations to uncover hidden patterns and knowledge within this data, driving further process improvements.

Several studies have demonstrated how machine learning can be applied to BPR to enhance process knowledge and operational performance. For example, machine learning can be used to analyze operational data, monitor processes, and measure performance, thereby providing actionable insights for continuous improvement. By integrating machine learning algorithms with ERP-generated data, organizations can optimize their business processes and make informed strategic decisions.

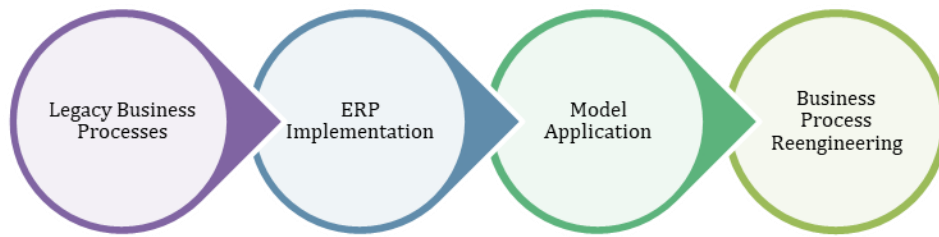


Figure 1-1: Concept Diagram

An ERP system consists of the following main modules:

- Accounting & Finance Management
- Human Resources Management
- Vendors & Purchase Management
- Production Management
- Customer Relationship Management
- Sales & Distribution Management

A thorough understanding of these modules is essential. Once the data is organized, it can be analyzed using machine learning algorithms. The models built in this study may include neural networks, association rules, decision trees, or regression models, depending on the nature of the data and the business processes under evaluation. These models are employed to uncover previously hidden patterns and insights in the data, providing valuable knowledge to managers and decision-makers.

This research specifically focuses on the impact of ERP implementation on Business Process Reengineering (BPR) in Sri Lankan firms using machine learning algorithms. Through a case study of Sri Lankan enterprises, the goal is to uncover patterns that reveal the impact of ERP implementations on business processes. Special attention is given to integrating new processes, functionalities, and version upgrades within established ERP systems, as well as addressing the unique challenges and opportunities associated with deploying ERP systems in the Sri Lankan context.

This study will be valuable for both academia and industry practitioners, facilitating informed decisions and strategies for effective ERP implementations aligned with the goals of business process reengineering in the Sri Lankan business landscape.

1.1 Problem Statement

The ERP industry is experiencing global growth as companies increasingly transition from manual processes to ERP systems like SAP, Infor, and IFS. However, in Sri Lanka, unique socio-economic, cultural, and technological factors significantly impact the implementation of ERP systems and their contribution to Business Process Reengineering (BPR). Challenges such as limited infrastructure, regulatory

constraints, workforce skill gaps, and cultural nuances can hinder the effective adoption of ERP systems. Additionally, Sri Lanka's diverse industry landscape, ranging from traditional sectors like agriculture to emerging sectors like information technology, poses unique opportunities for exploring the impact of ERP implementation on business processes across different sectors. Understanding these specific challenges and opportunities within the Sri Lankan setting will provide valuable insights into tailoring ERP implementation strategies and optimizing business processes effectively.

Despite the growing global interest in evaluating the impact of ERP implementation on BPR, research specifically focused on Sri Lankan organizations remains limited. Moreover, there is a notable gap in the use of machine learning algorithms to analyze this impact. Addressing this gap, the current study aims to evaluate and predict the impact of ERP implementation on business process reengineering in Sri Lankan enterprises using machine learning algorithms. By applying the CRISP-DM framework, the study integrates data collection, model development, and evaluation to effectively structure and analyze the impact of ERP on BPR.

The findings from this study will highlight the specific challenges and opportunities associated with ERP implementation in the Sri Lankan context. By leveraging machine learning algorithms and the CRISP-DM framework, the study will contribute to a deeper understanding of how ERP systems influence and enhance business process reengineering across various industries, offering valuable knowledge for both academia and industry practitioners.

1.2 Research Objectives

- 1) To collect and preprocess comprehensive data for assessing the impact of ERP implementation on business process reengineering in Sri Lankan enterprises.
- 2) To develop a predictive model using the CRISP-DM model.
- 3) To evaluate the accuracy and reliability of the proposed model by employing machine learning algorithms to refine predictive capabilities.

1.3 Expected Outcomes/Deliverables

The expected outcome focuses on using the CRISP-DM model to predict the business impact of ERP systems on Business Process Reengineering (BPR) initiatives in Sri Lankan organizations.

The CRISP-DM model is a machine learning method that provides a structured approach to business process improvement. It includes the following phases:

- Business Understanding
- Data Understanding
- Data Preprocessing
- Data Splitting

- Data Mining Techniques
- Model Evaluation

Architecture of the Model

1. **Business Understanding:** This stage involves understanding the business problem that the model is trying to solve. In this case, the problem is to predict the impact of implementing an ERP system.
2. **Data Understanding:** This stage involves collecting and understanding the data that will be used to train the model. The data could include information about the business's current processes as well as data from other businesses that have implemented ERP systems.
3. **Data Preprocessing:** This stage involves cleaning and preparing the data for use in the model. Tasks may include removing missing values, formatting data correctly, and scaling data.
4. **Data Splitting:** This stage involves splitting the data into 2 sets: a training set and a testing set. The model is trained using the training set, and its performance is assessed using the testing set.
5. **Data Mining:** This stage involves training the model on the training set. Various data mining techniques, such as decision trees, KNN, ANN, and techniques, could be used for this task.
6. **Model Evaluation:** This stage involves evaluating the performance of the model on the testing set. This ensures that the model is generalizable and capable of making accurate predictions on new data.

Input of the model: The model would take input data about an organization's business, such as its industry, size, and current business processes. It would also include data about the ERP system that the organization is considering implementing.

Output of the model: The model would produce a prediction of the business impact of the ERP system on the organization's BPR initiatives.

1.4 Chapter Synopsis

There are 6 chapters in this thesis. Chapter 1 outlines the problem, aim, and objectives of the study. Chapter 2 covers the literature review, which covers existing research on the Machine Learning-Based Impact Assessment of ERP System Implementation in Business Process Re-engineering. Chapter 3 presents the proposed solution, methodology, and interpretation of research findings. Chapter 4 discusses the implementation process, while Chapter 5 evaluates the study with results and discussion. Finally, Chapter 6 concludes the thesis and outlines suggestions for future work to enhance the findings of the research.

CHAPTER 2

LITERATURE REVIEW

A highly adaptable information infrastructure that can be quickly and efficiently developed or updated to meet changing business needs is what firms desire in the modern business environment. Additionally, they want hardware and software that can be integrated with other gear and software within their extended supply chain or organization. These systems need to be able to expand with the company while also enabling a high degree of interaction between business apps and internal and external data sources. Along with a variety of interface options like Interact, EDI, and telephony, these systems also need to operate in a multiple operating system environment. Therefore, it would be advantageous for organizations to purchase information systems that:

- Provide robust and affordable maintenance;
- Are openly distributed;
- Offer interchangeable information solutions;
- Reduce the time needed to deploy and continuously improve business processes;
- Define the system dynamically with minimal disruption;
- Improve system maintainability by using components from different release cycles;
- Easily support multiple business functions running different systems.

The expense of creating such systems may not be affordable for a single user organization. This explains the clear trend toward shifting away from in-house system development in favor of achieving the aforementioned benefits. The likelihood that a user organization will buy the processing capacity it requires from a computer center service provider has increased. Organizations will be increasingly focused on the broader concerns of obtaining cutting-edge technology and information systems that are economical, adaptable, and capable of managing enterprise business operations and functions in the 1990s and beyond. A majority of businesses who implemented the SAP system achieved so following a thorough and productive BPR effort. The employment of extensive technical and solution-oriented systems, like the SAP system, is therefore becoming more and more common in business strategies [1].

ERP systems, which fully integrate all of the data moving through a business, have been seen as a significant advancement in the corporate use of information technology since the 1990s. They improve organizational cross-functional efficiency and effectiveness. ERP is the foundation of a firm. Many of a company's internal business activities are automated and integrated by this cross-functional enterprise system. Business process reengineering is controlled by ERP implementation [2].

BPR and IT frequently work together since new technology enables new ways of working. It can be wise to start by addressing basic management and business

difficulties. IT can help support new organizational structures and re-engineered processes, but it has relatively little impact on these problems in many businesses. Additionally, BPR is a shorter procedure, and the benefits accrue more quickly for businesses that need to improve immediately owing to low profitability. After reorganization and BPR, the strategy for IT investment may completely change. Basic business concerns could be missed if SAP is employed as a BPR tool, as European line managers did in the [3] case study. Even though the software may have more sophisticated business procedures than the various and outdated programs it replaces, the company may not be able to take advantage of the prospect for substantial business improvement because of the effort required to implement the software. Longer term planning allows the company to better align SAP software with the (re-engineered) business needs. Additionally, the combination of BPR and IT investment may give the company a competitive edge.

Business Process Reengineering can be defined as the analysis and design of workflows and processes within and between organizations. BPR has the potential to lead businesses into a new level of competitive effectiveness when applied properly. Although until it is incorporated into a broader perspective of the company as a whole, which needs to become integrated in the corporate culture, the reengineering of particular processes will always have a limited impact. Data mining is a technique that enables business practitioners, senior managers, and decision makers to extract relevant, useful, and previously hidden knowledge from an organization's database. This knowledge can be managed carefully to produce the quantity of data needed to put Business Process Reengineering into practice [4].

By definition, business process reengineering is the quick and significant redesign of strategic, value-added business processes and the organizational structures that support them in order to optimize a company's productivity and workflows. Any BPR tool must therefore offer a platform for business unit integration. It is in the best interests of management to assess a number of design scenarios and determine the advantages, disadvantages, implementation challenges, and expenses related to each. Ideally, a quantitative assessment of the effectiveness of the business processes of the organization and an economic study of its business strategies are needed. For IT investment decisions to inspire confidence and interest, some kind of justification supporting business decisions to redesign and invest in IT is required. Multiple companies have discovered that SAP gives them the ability to take leadership in the business environment, give clients more options, streamline operations, and keep costs under control. A adaptable platform that may be applied in a wide range of ways is offered by the SAP open architecture. Business and system integration service providers need appropriate platforms for application development and deployment. They deal with the difficulty of incorporating technology-driven systems into business processes [1].

[5] emphasize that the BPR process is a micro-level activity that is crucial and cannot be disregarded by organizations wishing to deploy ERP. Because the BPR procedure is expensive and time-consuming, most organizations choose to use it. [6] offers a conceptual paradigm to investigate BPR stories and empirically support the connections between BPR and IT.

2.1 Enterprise Resource Planning (ERP)

Enterprise resource planning is an emerging concept in the current globalised and digitalised business environment. As businesses operate more globally, software is being used more often to increase business efficiency. One of the key factors to winning in today's market is creating more value than competitors, and creating value requires timely and accurate decision-making in all business events and processes, including production, cost monitoring, selling and distribution, and pricing. Decisions must be based on well-integrated information from all areas of the company, and enterprise resource planning systems are vital for integrating all business operations. Management can gain control over the organization's business intelligence by combining supply chain procurement, manufacturing, finance, sales, and distribution into a single system [7]. As a result, ERP is already an essential element of the company that improves business operations with standardised solutions, increasing the effectiveness of business events.

Organizations can manage resources among a variety of diverse company activities with the tools and strategies that ERP software application offers. By interpreting data and documents, it gives the proper direction to the planning, carrying out, and controlling of functions. Using the right software improves the administration of operations processes for scheduling business activities, purchasing, material management, and budgeting [8].

Inventory management and control software was developed in 1960 by combining information technology and business processes to ensure that warehouses had an adequate amount of inventory [9]. Later in the 1970s, inventory control was integrated with manufacturing and operations to create schedules for inventory purchases and operations management. Material Requirements Planning (MRP) was the name of this system. In 1990, the enterprise resource planning system was developed as a comprehensive solution that integrated manufacturing, accounting, marketing, inventory control, product distribution, and product planning [9]. This comprised cross-functional operations and gave an overview of business events. ERP firms now offer cloud-based solutions with further modifications to a wide range of customers across multiple industries. ERP systems have a greater influence on the company, its employees, and its business operations than basic information systems. They are also more comprehensive and sophisticated [10].

SAP, Microsoft Dynamics, Oracle, INFOR, and Sage are the leading producers in the market. Oracle ERP is the market leader with a 5.78% market share. With a 2.39%

market share, SAP Business One is another popular system [11]. Modern ERP solutions offer both cloud-based and on-premises server options. Cloud-based ERPs, which store data on vendor servers, are accessed by clients via browsers [9]. The ERP sector will grow more dynamic and economical as technology develops. ERP solutions are expected to enhance automation-driven business decision making, big data analysis, and enhanced reporting, according to industry analysts [9].

2.2 Business Process Reengineering (BPR)

There is certainly that business process re-engineering improves company processes. Despite this, it is costly, time-consuming, and very challenging. To achieve strategic targets, objectives, and goals, an organization, enterprise, or corporation is made up of a sequence of interrelated and organized business processes and activities. Managing these processes effectively and efficiently is necessary. To put it another way, business processes are an organized method of organizing tasks and reaching goals. Owing to the ever-changing nature of business, organizations also frequently develop, change, or broaden their market reach. This has an impact on the business operations, thus the procedures need to change to better meet the needs of the organization. Additionally, organizational procedures have been important in controlling and increasing production ever since the first industrial revolution, when Henry Ford created the assembly line. Process science thereby became a potent instrument for increasing process productivity, both conceptually and practically, and gave rise to a variety of innovative tools and approaches like business process re-engineering.

Moreover, a business process is influenced by both internal processes within the same organization and external events as a dynamic component. As a result, business process management evolved from the first business process re-engineering in the 1980s to a widely used management technique, eventually emerging as a standard for corporate management. Business process management techniques also enhanced the tracking and regulation of profitability, service delivery standards, productivity, and other corporate goals.

Business Process Re-engineering (BPR), the most modern and promising approach, focuses on implementing adaptable, streamlined processes that function at the inter-functional, intra-functional and inter-organisational levels. Additionally, it has been stated that knowledge-based systems facilitate and impact how BPR is applied in individual businesses [12].

The primary objectives of an organization can be defined as follows: removing non-value-added tasks; empowering employees to work in a collaborative environment; simplifying and increasing the flexibility of processes; and ultimately, enhancing financial controls and reducing operating costs. The most successful BPR adopters, however, view these objectives as secondary to the main objectives that drive an organization's competitiveness and capacity to function effectively in progressively

challenging market environments. Adherence to quality standards, effective supplier management, and responsiveness to customers are among these objectives. As the new business processes have built-in flexibility, agility, and responsiveness, BPR can result in overall benefits in value, quality, customer service, and productivity.

Most of BPR operations rely heavily on IT, and with the arrival of technologies like the Intranet, data warehousing, and knowledge-based systems, significant progress can be achieved in managing key corporate issue areas [13].

In addition, the integration of machine learning into enterprise resource planning (ERP) systems has transformed business process reengineering (BPR) by enhancing automation and digital transformation. Machine learning techniques enable organizations to analyze business processes more effectively, providing data-driven insights to streamline operations. This has significantly improved productivity, efficiency, and adaptability in business processes. While the application of machine learning within ERP systems presents challenges, such as integration complexities, it offers solutions that enhance the responsiveness and flexibility of business operations. By focusing on analyzing and restructuring processes through machine learning, organizations can achieve greater efficiency and make informed decisions that align with their evolving objectives [14].

Artificial intelligence and machine learning are rapidly demonstrating the advantages of taking advantage of existing data. Because of its significance, data can be used to uncover hidden patterns and offer creative solutions to difficult real-world problems. According to the hypothesis, there is a chance to leverage the process data through machine learning to automate business process re-engineering because they are readily available. It is possible that the data will need to be prepared and may not be provided right away.

2.3 Data Science and ERP Systems and BPR

ERP systems generate vast amounts of structured and unstructured data across various business functions by leveraging data science methodologies, organizations can analyze this data to uncover patterns, trends, and insights that were previously hidden. In this context, ERP systems are being exposed to big data more and more, allowing for the rapid analysis of greater volumes of both structured and unstructured data from various systems. In order to understand and explore data, big data analytics necessitates a larger usage of predictive analytics to find hidden patterns and their relationships [15]. Analytics-driven automation and decision management in high volume, front-line decision-making may now be explored in new ways owing to the development of big data and predictive analytics. To identify those hidden pattern used various data science techniques. Among them, Data mining emerges as the foremost technique within the realm of data science.

Data mining, a subset of data science, involves extracting valuable information from large datasets, enabling predictive analytics and informed decision-making. Through sophisticated algorithms and machine learning models, data mining can enhance the functionality of SAP ERP systems, providing real-time analytics, forecasting, and optimization. ERP and big data allow enterprises to have stronger and more comprehensive in-scope best practices, as explained in [16]. The ability to adopt more quickly and with greater quality will have a significant influence on the organization. In order to assist decision makers in making exceptional decisions, Business Intelligence (BI) tools and methodologies are also used as an addition to ERP systems. In fact, BI may use data mining techniques to uncover hidden patterns and undiscovered information, and it can also be used for data visualization.

OLTP-based software applications, such as SAP and Oracle, are used to source operational data from a variety of business operations. These programs carry out business-specific procedures associated with every function and monitor their implementation throughout the organization [17].

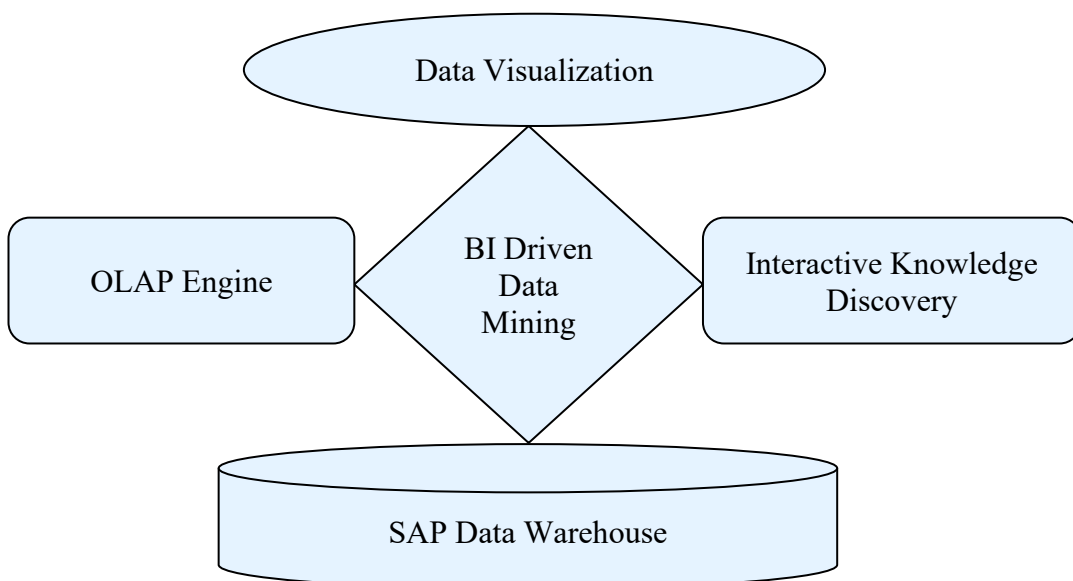


Figure 2-1: Data Visualization Tools for SAP BI Systems

Business Process Reengineering can be analyzed through data mining. A business process is a set of actions taken to generate additional company values, and its ongoing development in line with corporate objectives is essential for surviving in a rapidly evolving business environment. Finding out whether a change in business processes has a beneficial impact on company goals, whether there are issues with the change, what the causes of the issues are, what solutions are available, and which ones should be chosen can be challenging. A novel approach for successful business process reengineering is made possible by big data analytics along with goal-orientation, which work together to extract insights from a vast amount of data in a goal concept [18]. In order to significantly increase performance, efficiency, and customer satisfaction, business process reengineering is important. In this context, data science plays a crucial

role by providing the analytical tools and techniques necessary to extract valuable insights from vast amounts of organizational data. By applying data mining methodologies, organizations undergoing BRP initiatives can uncover hidden patterns, correlations, and trends within their operational data. These insights enable informed decision-making and facilitate the identification of process inefficiencies or areas ripe for improvement. Moreover, data science empowers BRP efforts by offering predictive analytics capabilities, allowing organizations to anticipate future trends and adapt their processes accordingly. Techniques from statistics, data mining, machine learning, databases, visualization, ethics, and high-performance computing are all combined in the field of data science. Business Process Management (BPM), Workflow Management (WFM), Business Process Reengineering (BPR), Operations Research (OR), and other process-centric methodologies are all included in the larger field of process science [19].

The importance of big data and analytics is explored in [20]. This kind of demand appears to be growing as businesses increasingly seek out highly qualified and data-savvy personnel. Making connections between analytics and business processes is crucial for decision-making, but doing so now requires handling large amounts of data. Examining and discussing how academics implement curriculum on developing big data and analytics is so essential. Large software corporations like SAP, Oracle, and Microsoft fund initiatives to offer "hands-on" curricula that academic institutions could adopt in order to facilitate the spread of such curricula [21].

2.4 Success Factors for the Effective Usage of an ERP System

System success is one of the most pervasive research areas in the field of information systems. Prior studies have focused on success measurement, success antecedents, and success and failure explanations. But as several new kinds of information technology appear, the issue of success emerges. Since the cost and risk of these important technological investments are comparable to the possible rewards, success in ERP systems assumes a specific urgency [22].

Many businesses across the world discover it challenging to understand the success aspects for setting Enterprise Resource Planning (ERP) systems into place. A company can use an ERP system to link all of its essential business activities, boosting productivity and helping it stay competitive. But without the system being properly implemented, the expected benefits of higher productivity and competitive advantage would not materialize [23].

Data-driven success criteria for improving the use of ERP systems after deployment have been the subject of several scholarly publications. These include: active top management commitment; resistance to change; ERP post-implementation resistance; reduced complexity of the ERP used; improved IT infrastructure in the company; early detection of hidden costs of ERP modifications; efficient ERP system training; and efficient ERP system usage.

Resistance can be described as a situation that discourages the entire change process in an organisation, by hindering its initiation, its successful implementation, and by increasing its costs [24]. Resistance to change is one of the concepts that is commonly mentioned in the literature on change management. In order to better understand the success determinants of ERP deployment, this study will examine user resistance, which is a major factor leading to the loss of return on ERP implementation [25]. The proposed changes will not be successful if employees are resistant to change, which will have major consequences. The data shows that one of the reasons organizational change fails is employee resistance to change. In literature, there are a number of things that can lead to resistance, including emotional loyalty, a lack of skills, subjective norms, and deeply held values. Opposition of this nature could prevent the implementation of new incremental procedures and result in underutilization of the ERP. The most common and commonly stated sources of resistance are a lack of confidence among top management and consumers, as well as reluctance to change [26]. Furthermore, most employees don't understand why change is necessary, and top management finds it challenging to convey this to them. The personnel is terrified by the sudden change, which restricts their ability to adapt to the new culture [26]. Therefore, it is primarily the responsibility of senior management to identify the environmental variables that influence resistance within the company.

ERP post-implementation resistance, as 49% of ERP organizations say that their ERP process deployment is a never-ending show, even after the initial ERP implementation. After completing the initial implementation, organizations need to get ready for a more profitable journey with the ERP system, which includes nearly every element of the integrated system. If the organization could gain much more, why make such a big claim? To properly manage incremental processes and get the most out of the ERP investment, it is essential to comprehend post-implementation resistance to them. [27] states that people's barriers, business process problems, and technical (information technology) problems are the key causes of resistance and problems while implementing an ERP system [27]. The main stakeholders in human hurdles include senior management, process owners, managers, users, and ERP consultants. Thus, it can be claimed that human factors, such top management's passion for new procedures and process owners' participation in user issues, may influence resistance. Krasner highlights how important it is to pay more attention to the resistance that individuals have to ERP subprocesses after they have been implemented. Although personnel problems persist after first deployment, factors such as continuous training and support, reporting, business success, and system migration are prioritized more [27]. Both regular and skilled users have established their own routines and comfort zones at work, which prevent them from stepping outside and accepting change. To effectively manage them and get the most out of the ERP investment, it is essential to understand the post-implementation resistance to incremental processes and, consequently, identify the success factors that influence the efficient use of an ERP system.

In every business event, the top management of an organization actively commits to directing the people and resources to fulfill the corporate goal. Therefore, this leadership and involvement are essential during an organizational transformation. One element that has a direct impact on the outcomes and success of the implementation of ERP is top management participation [28]. An organization needs a strategic vision in order to remain successful over the long term and adjust to change. Without the genuine commitment and backing of top management, which is considered a superior transformation facilitator, organizations cannot undergo significant change. The literature highlights that information technology adoption and organizational culture changes require effective leadership. Furthermore, studies show that leaders' attitudes and actions play a significant part in how well staff members comprehend and, consequently, embrace IT change [29]. The management's vision and actions during the implementation of new incremental ERP processes will have an impact on the level of internal resistance. According to enterprise management literature, organisational culture may be purposefully managed and shaped by leadership, which in turn facilitates the effects of leadership on 13 organisational changes. ERP success can be increased by the management's effective leadership abilities to proactively develop an organisational culture. Therefore, one of the key elements for the efficient use of an ERP system can be regarded as top management motivation, excitement, progressive feedback, correct attention, support, and enough communication.

Even though organizations all over the world utilize ERP solutions, there are more and more obstacles to overcome when enforcing new procedures [30]. Significant project failures and cost overruns occur as a result of a lack of understanding and awareness regarding how to manage these [30] challenges during implementations due to the ERP system's complexity. Additionally, even with large expenditures, extended timelines, and resources dedicated to the ERP overall system, certain processes fail to meet business requirements [30]. The complexity of ERP can sometimes cause implementation resistance and criticisms that outweigh any benefits a company could receive. Effective use of the ERP and sound decision-making depend on users' ability to easily understand the data and information that are presented. Because ERP deployment projects are made up of many interconnected submodules that are subject to continuous modification, they have the characteristics of a complex system, which makes governance complicated. An further major factor that could influence the complexity identified in the initial phases is the scale of the process that will be implemented in the ERP. Changes from different stakeholders shouldn't happen too often, and the scope of implementing new processes within the ERP must be well defined. Any deviations from the agreed-upon scope can result in delays, rework, and increased costs, all of which may ultimately lead to project failure. The following are the three primary reasons why the ERP has become more sophisticated. They are human behavior, system behavior, and ambiguity. An ERP is inherently complex since it is made up of a number of interrelated submodules, parts, and programs. Issues could occur if any of these parts are detached. The nature and complexity of the ERP must be assessed in order discover how it might impact the resistance. Diverse

business processes, growing client expectations, and strict software requirements have all contributed to the complexity of enterprise systems. Therefore, it may be defined as the challenge of completing a business event using the system. One of the primary strategies for minimizing ERP complexity is to provide user support during a transaction or business process data entry. This can be achieved by highlighting required fields, showing assistance, warning, or error-prevention instructions, or by suggesting concepts like auto-completion or the next steps. This approach can only assist users spend less time acquiring the skills to transfer their specific field and process expertise to the ERP system, even though it is quite effective in reducing the complexity of the ERP interface.

The overall effectiveness of ERP implementation is influenced by 38.4% of the organization's technological infrastructure, with better infrastructure leading to more successful outcomes [31]. A solid IT infrastructure supports the sustainability and maintenance of the existing ERP system within the organization. It is costly and necessitates a large financial investment to maintain an organization's technological competency improvement. An organization is unable to deploy an ERP or access and exchange data across all organizational applications without properly established server technology and an open database connection. Despite the fact that it is costly for a business, proper IT infrastructure is recognized as an essential element from the beginning of ERP implementation and throughout the remainder of the solution's life cycle [31].

Pre-identifying the hidden costs associated with ERP changes is crucial, as ERP systems often involve uncertainties in acquisition and hidden implementation costs. When putting an ERP system in place, both large and small businesses must take finances into account. They also highlight how companies implementing ERP solutions may overlook hidden costs.

Citing a source [32], the passage identifies several typical hidden costs that can significantly impact the overall cost of ERP implementation:

- **Training:** The cost of training is mentioned as the most underestimated hidden cost. Training the entire workforce on a new system is described as having an enormous cost.
- **Integration and Implementation:** The passage notes that integration and implementation costs are frequently disregarded, possibly contributing to underestimation of overall expenses.
- **Data Conversion:** The underlying cost of data conversion is highlighted, and it is mentioned that costs associated with transferring data are often not recognized.
- **High Consulting Costs:** Many organizations may not budget consulting costs effectively, leading to unavoidable high-consulting costs during the ERP implementation.

- **Project End Date:** The idea that the ERP project will conclude on a specific date is one expense that is commonly overlooked, according to the passage.

Effective training on ERP system, ERP system implementation and operation success depend heavily on training. Similar to all new technologies in an organization, ERP systems require training for staff to use appropriately and effectively [33]. Therefore, it has been considered that the most significant factor in the success of an ERP implementation is ERP training. Most ERP concerns were related to people-related issues. Therefore, a successful ERP implementation and operation depend heavily on training. ERP training enhances the ERP system's optimization. In order to ensure reliable interpretation of the responses, they employed 14 qualitative interviews and 217 survey questionnaires from manufacturing organizations. The results show that training is crucial for both maximizing the potential of an enterprise resource planning system and gaining software expertise. [34] states that the benefits of training extend beyond only teaching system usage. They proved that training is particularly advantageous since it can increase user acceptability and develop a positive attitude toward the system.

The effective implementation of ERP systems requires that they be dynamic, scalable to support organizational expansion, and will set best practices for organizations as the standard for all business operations [35]. Additionally, ERP systems can supply and collect the accurate data required to increase the effectiveness of business processes throughout the entire firm. However, ERP systems are not always efficient in their application, even with their many advantages. Since most of the benefits of ERP software are yet unrealized, most companies find it difficult to adequately justify their investments in it. About 20% of ERP installs cannot be completed, and 25% of them cost more than planned, according to [36]. The general dissatisfaction with the effectiveness of ERP systems is caused by a number of causes, one of which is a lack of knowledge about the system's capabilities. A misunderstanding of the ERP system's potential is one of several factors contributing to the overall dissatisfaction with its efficacy [37]. However, resistance to change is removed by improved ERP system usage. In this way, the researcher expects to find out the success factors for using an ERP system effectively in the post-implementation phase.

2.5 Machine Learning Approaches in ERP and BPR

Organizations aiming to improve their performance often need to consider business process reengineering (BPR) initiatives. A significant challenge lies in the large volume of process data generated during ERP implementations, coupled with the wide variety of features within these datasets, which increases the complexity of analyzing and improving business processes. Machine learning approaches can assist in addressing this challenge by predicting the impact of ERP implementation on BPR outcomes and uncovering valuable hidden patterns in process datasets [38]. The study [39], examines the integration of machine learning algorithms into ERP systems. It discusses the use of predictive analytics and highlights recent advancements in

machine learning for enhancing ERP functionalities. The study emphasizes that machine learning integration transforms ERP systems into intelligent platforms that improve organizational performance. Furthermore, it offers insights for stakeholders on leveraging machine learning for better decision-making and demonstrates how ERP systems can adapt to changing business requirements, enabling more efficient and flexible operations.

The study [38] proposes a machine learning-based framework to predict the impact of ERP implementation on BPR in Sri Lankan organizations. A real dataset of ERP-implemented business processes, along with their relevant features, was collected for this purpose. Supervised learning algorithms, such as classification, regression, and feature selection, were used to identify significant patterns and relationships within the dataset. These patterns were then evaluated to assess their contribution to predicting key BPR outcomes, such as process efficiency, cost reduction, and operational improvement.

Business process re-engineering (BPR) plays a key role in the deployment of enterprise resource planning (ERP) systems. A range of methods are employed for this kind of re-engineering because the optimal ERP solution can only provide an 80 percent match with the organization's current workflow. The study [40] provides a few sample ERP implementations to demonstrate several business BPR types, from small-r to big-R, that are used during ERP implementation. Given that the different BPR approaches are grouped according to the implementation strategies used by large organizations, it is certainly a precursor for every ERP-implementing organization that is the subject of the study. Additionally, the typical issues that arise while re-engineering for an ERP implementation are discussed, along with the recommended solutions that are based on previous research.

The [41] study on the ERP-driven transformation of business processes proposed to investigate the use of machine learning techniques to develop business process reengineering (BPR) recommendations. The reengineering process focused on rethinking and improving decision-making operations within ERP implementations. Initially, the real objectives of the reengineering process were identified, and indicators reflecting these goals were defined. Subsequently, machine learning techniques were applied to analyze ERP process data, extract meaningful patterns, and provide actionable insights to guide the BPR effort more efficiently.

Machine learning, often referred to as an evolution of data mining, is the computer-assisted process of analyzing large datasets to uncover hidden patterns and insights. It builds upon traditional data mining techniques by incorporating advanced algorithms capable of learning and improving over time. When it comes to business process reengineering (BPR), machine learning is a powerful technology that has the ability to assist firms in concentrating on the most important elements of their ERP data. These tools can predict future trends and behaviors, enabling businesses to make proactive,

data-driven decisions. Most organizations implementing ERP systems already collect and refine vast amounts of process-related data, which can serve as a foundation for supporting reengineering efforts. Machine learning models extract essential knowledge hidden within these extensive datasets, offering actionable and meaningful patterns, profiles, and trends. By leveraging techniques such as neural networks, supervised learning, and genetic algorithms, machine learning provides efficient solutions to complex business questions that were traditionally too time-consuming to address. This makes it an invaluable tool for predicting the impact of ERP implementations on BPR outcomes [4].

KNN may be simple to implement, but as the dataset grows, the efficiency or speed of the method drops rapidly. With the help of organizational, technological, and human factors as predictors, alternative conceptual model is offered to forecast user satisfaction [42]. The K-Nearest Neighbor (KNN) Classification algorithm was applied to predict user satisfaction. An ANN (0.6053) approaches, KNN provides good prediction accuracy in most circumstances and a low average error (0.25).

Another study conducted by Rouhani and Ravasan [43] used Artificial Neural Network (ANN) and Expert systems to estimate ERP post-implementation success based on organisational profiles. This study aimed to establish a link between organisational profiles and ERP success levels. That is, no one has yet to bridge the gap between the type and profile of organizational aspects using the articulation capabilities of ANNs. With a strong correlation coefficient of 0.744, the trained expert system makes predictions. Furthermore, the total correct classification rate of 0.685 suggests that the prediction power is good.

The decision tree method was suitable for this kind of problem since it divided process activities into flow scenarios and searched the supplied process events for hidden patterns [29]. There could be other deviations from the initial process flow, but the most frequent pattern indicates one possibility of the process flow situations. Machine learning applications also included the capability to predict the behavior of processes. Multiple algorithms were employed to solve it, according to the review [44], [45].

Machine learning, as the next-generation tool, leverages previously underutilized ERP data repositories to help organizations gain a competitive advantage in increasingly dynamic markets. Although machine learning is a cutting-edge technology, as demonstrated by [13], its use may be efficiently managed and maximized by incorporating its methods into the BPR framework, allowing businesses to improve workflows and meet performance goals.

2.6 Computer Science Aspects of ERP Implementation

Two approaches were presented in [46], [47] to explain the use of DM in BPR. In the first approach, it was emphasized that an integrated attitude between the Data Mining (DM) process and Business Process Reengineering (BPR) is essential for successfully

applying DM techniques to BPR. In this regard, the use of DM was decided at every step of the integrated BPR methodology. DMbBPR is the name of this proposed model. The second method introduced a new combinational model of process mining in an integrated form based on the CRISP-DM standard process and the knowledge management cycle inside the framework of process monitoring architecture. By using this innovative combinational model, business processes may be identified and analyzed using the DM process, leading to a thorough understanding of process improvement. The case study results produced by applying the combinational model were obtained using a sample of the SIPOC process dataset. In order to facilitate process reengineering and business process improvement, this model's primary goal is to integrate knowledge management processes with CRISP-DM standard process within a framework of process monitoring architecture. These two new approaches in this research may point to a connection between BPR and the DM process. The key idea is that both strategies should be taken into account at the same time in order to identify, evaluate, and enhance business processes in a way that will improve the final outcome of DM application in BPR.

Exploration and analysis of huge volumes of data stored in databases to find significant correlations, patterns, and trends is known as data mining. Business intelligence is one of the key applications that data mining approaches. Effective market analysis, customer feedback comparison, product similarity, customer retention, and strategic decision-making are all possible with data mining. To explore and evaluate data, data mining employs numerous statistical and predictive techniques. These techniques include classification trees, neural networks, regression trees, cluster analysis, association rules, and linear regression. A technique for DM is the Cross-Industry Standard Process of Data Mining (CRISP-DM) [48].

Data Mining (DM) techniques can be used to discover and analyze business processes in Ghanadbhasi's model, generating valuable insights for process improvement. This method is taken into consideration as a unified combinational architectural model of process monitoring that is based on the CRISP-DM standard in DM processes and knowledge management in business processes. The second strategy explains how data mining tools are applied to find and examine business processes [49], [50].

2.7 Overview of the Literature

Although the methodical review of literature analysed a number of previous research publications, journals, books and other materials, the following studies were selected as the most relevant articles for this particular study.

Reference	Outcomes/Findings	Limitations
[16]	<p>Combined ERP and big data creates a capable and powerful technology platform and it has been identified that,</p> <ul style="list-style-type: none"> • Allows organizations to achieve deeper insights into business data, leading to better-informed decision-making processes. • Streamline the business processes. • Improved Competitiveness. And operational Efficiency. 	<p>Not address how the integration of Big Data and ERP systems will affect existing functionalities, introduce new capabilities, and impact the overall ERP lifecycle.</p>
[18]	<p>Proposed a new modeling framework that helps with the why, what, and how questions of business process re-engineering by using big data analytics and a goal-oriented approach.</p>	<ul style="list-style-type: none"> • Help to redesign better business processes in terms of reliability, preciseness and traceability. • Not support automatic transformation from as-is business processes to to-be business process.
[15]	<p>The introduced new application framework by integrating big data analytics and predictive analytics to the organizations to build horizontal processes. ERP systems should be flexible, analytical, and adaptable, according to research, so that people and processes may become more analytics-driven.</p>	<p>Focus on crucial variables to minimize model implementation costs, avoiding the inclusion of too many variables that do not significantly enhance predictability. And not involve integrating predictive analytics for business processes on big data.</p>
[38]	<p>Introduced new framework using data mining techniques (classification, and feature selection) and identified valuable patterns hidden in the large number of processes for the process improvement.</p>	<p>Not consider the other data mining techniques (except classification, and feature selection).</p>

[40]	The most effective approach to revamp business processes is to implement ERP and BPR. The ERP-implementing organization's organizational needs and limits should guide the selection of an appropriate BPR approach.	Consider ERP integration with supply chain management and not align with other business processes.
[51]	Proposed a framework for automatically extracts valuable patterns and recommends process improvement suggestions using classification (decision tree algorithm) DM techniques.	Other classification algorithms not applied to extract valuable patterns for recommending process improvement suggestions.
[46]	Proposed a model (DMbBPR) that combined CRISM-DM model and identified that business processes to achieve good knowledge to process reengineering in business process improvement.	Consider only the DM process and BPR not consider ERP.
[52]	Incorporating the CRISP-DM process as a fundamental component of the model, this study aims to establish effective interaction between ERP implementation and business process reengineering, ensuring a comprehensive analysis of their impact and fostering successful integration within organizational processes.	The introduced framework does not provide a flexible data mining solution integrated into business processes within the context of modern BPM frameworks.
[53]	As the level of adaptation expands, the correlation between ERP's organizational fit and deployment success changes from "positive" to "negative". Therefore, organizational fit has a significant impact on how well ERP rollout goes.	<ul style="list-style-type: none"> • Concentrated on a small set of factors that are essential to the effectiveness of implementing enterprise resource planning. • Implementation success was defined using perceived project matrices, omitting factual aspects of success outcomes.

		<ul style="list-style-type: none"> • Has a common bias because the same respondent recorded both the independent and dependent variables.
[54]	<p>Users may find it difficult to use the system when it comes to ERP for a number of different reasons. Within the viewpoints of people-, system-, and interaction-oriented approaches, factors for user resistance have been identified, including gender, values, user interface, performance, dependability, and the connection between people and systems. Additionally, senior management needs to be aware of the fact that perceived danger and habit are important factors in user resistance.</p>	<ul style="list-style-type: none"> • Finding sufficient literature that particularly addressed user resistance in the ERP domain was difficult. • The concept of user resistance is somewhat wide, and not all companies or situations will experience the same levels of resistance or the conclusions provided in this study.
[30]	<p>“Nine critical factors have been identified as contributing to the failure of ERP implementations: excessive customisation, dilemma of internal integration, poor understanding of business implications and requirements, lack of change management, poor data quality, misalignment of IT with business, hidden costs, limited training and lack of top management support.”</p>	<ul style="list-style-type: none"> • As a topic for future research, the paper suggests creating a framework to address each implementation of ERP failure factor in its entirety based on how frequently it occurs in industry.
[24]	<p>This research has demonstrated that the human factor, or the operators' or users' refusal to completely adopt the technology and to fully harness the technology's potentials, are significant obstacles to the implementation of improvements in Malaysian manufacturing organizations. To solve this issue, management must launch a planned</p>	<ul style="list-style-type: none"> • The low response rate and time limitation result in a small sample size. • The person who completed the questionnaire may not be representative of all users within the organization because only one questionnaire was

	<p>campaign to inform users of the new system's potential advantages. This could, in a variety of ways, lessen potential opposition and increase the possibility that the implementation would succeed.</p>	<p>requested from each company, particularly for the section on user satisfaction.</p> <ul style="list-style-type: none"> • The research excluded real aspects of implementation success outcomes because it was impossible to obtain actual data from the participating organizations, and instead defined implementation success using perceived project metrics.
[55]	<ul style="list-style-type: none"> • Top management support was one of the most frequently cited critical success factors during ERP implementation. • Organizational structure and culture also highly affected ERP implementation. 	<ul style="list-style-type: none"> • The study was done only in the content of Higher Education Institutes
[56]	<p>The findings reveal that users regard 11 of the 13 CSFs found in the literature as important for ERP system implementation. Seven of the CSFs were classified as the most important from a user perspective, namely, project team, technical possibilities, strategic decision[1]making, training and education, minimum customization, software testing and performance measurement. Users regarded 2 of the 13 CSFs as not important when implementing an ERP system, including organizational change management and top management involvement.</p>	<ul style="list-style-type: none"> • The respondents come from a single country, industry, and organization. Since the results could vary depending on the situation, other companies, sectors, and countries should be included in future studies. • Only evaluates existing CSFs from a user perspective rather than identifying new ones and/or the underlying reasons using more qualitative research.

In the current literature review, while there is substantial discussion on the benefits and challenges associated with Enterprise Resource Planning (ERP) systems and Business

Process Reengineering (BPR), there is a noticeable lack of emphasis on addressing the resistance to change within organizations during both the implementation and post-implementation periods of ERP systems. This gap in research overlooks a crucial aspect that often hinders the effective usage and maximization of returns from ERP investments. Additionally, the existing literature does not sufficiently explore how leveraging data mining approaches can be used to evaluate the impact of business process reengineering within organizations. These limitations in the current research highlight the need for a study that specifically focuses on addressing these gaps. Therefore, this study aims to contribute to the literature by providing a comprehensive analysis to evaluate the impact of ERP implementation on BPR, with a particular focus on Sri Lankan organizations. Additionally, the study aims to explore the potential of leveraging data mining approaches to evaluate the impact of business process reengineering, thus addressing the limitations of the current research and providing valuable insights for practitioners and researchers in the field.

CHAPTER 3

PROPOSED SOLUTION

3.1 Research Contribution

The study addresses a significant gap in existing literature by focusing on the impact of ERP implementation on business process reengineering (BPR) specifically in Sri Lankan organizations, an area that has been overlooked in previous research. This fills a void in the field of ERP implementation and BPR by addressing the identified research objectives in a targeted manner.

A key innovation of this study is the introduction of a robust model, integrated with the CRISP-DM model, to systematically evaluate the impact of ERP implementation on BPR in Sri Lankan organizations. This comprehensive model not only enhances theoretical understanding but also offers practical insights for practitioners involved in ERP implementations within the Sri Lankan context.

By leveraging machine learning methods, such as neural networks and decision trees algorithms, the study rigorously evaluates the effectiveness of these techniques in analyzing the impact of ERP implementation on various business processes. Through empirical validation and in-depth analysis, this study contributes to a deeper understanding of the intricate relationships within ERP projects, providing actionable guidance for managers and researchers aiming to optimize ERP implementations in Sri Lankan organizations.

Additionally, the study aims to provide valuable insights for practitioners involved in ERP implementation and BPR in Sri Lankan organizations. By analyzing the impact of ERP implementation on BPR using machine learning algorithms, the research findings are expected to offer practical applications and actionable recommendations for enhancing ERP implementation strategies and optimizing business processes within the Sri Lankan context. These recommendations may include tailored approaches for overcoming resistance to change, optimizing resource allocation, streamlining workflow processes, and leveraging ERP functionalities to drive organizational growth and efficiency.

3.2 Proposed Method

Machine learning algorithms are proposed to assist process owners, business managers, and consultants during ERP implementation, focusing on identifying success factors through data-driven patterns. The proposed research will apply machine learning algorithms within the CRISP-DM framework to systematically predict the impact of ERP implementation on Business Process Reengineering (BPR) in Sri Lankan organizations. The following detailed steps outline the methodology:

1. **Data Collection:** Quantitative data will be captured from Sri Lankan enterprises through surveys. A questionnaire will be shared with organizations that have implemented or are in the process of implementing ERP systems (such as SAP, IFS, Infor M3, Oracle, Sage, Microsoft Dynamics, etc.). The survey will capture data on the ERP involvement of organizations, the ERP background of organizations, and the impact of ERP implementation on BPR.
 - i. **Target Participants:**
 - **Participants:** The following types of management-level individuals from organizations that have implemented or are in the process of implementing ERP systems:
 - Top-Level Managers: Chief Operating Officer (COO), Chief Financial Officer (CFO), Chief Information Officer (CIO), Chief Executive Officer (CEO)
 - Middle-Level Managers: Department Heads, Regional Managers, General Managers
 - First-Line Managers (Operational Managers): Supervisors, Team Leaders, Office Managers
 - Functional Managers: HR Manager, Marketing Manager, Finance Manager, IT Manager
 - **Sample Size:** Aim to survey at least 10 organizations (150 dataset) to ensure a diverse and representative sample.
 - **Industry Coverage:** Include participants from various industries such as manufacturing, retail, finance, healthcare, and logistics to cover a broad spectrum of ERP usage.
 - ii. **Data Collection Instrument:**
 - **Questionnaire Design:** Develop a comprehensive questionnaire with both closed-ended and open-ended questions to capture detailed quantitative data.
 - **Distribution Method:** Distribute the questionnaire via email and online survey platforms. Follow up with phone calls or personal visits if necessary to ensure a high response rate.
 - iii. **Quantitative Data Points:**
 - **ERP Involvement:**
 - Type of ERP system implemented (e.g., SAP, IFS, Infor M3, Oracle, Sage, Microsoft Dynamics).
 - Duration of ERP implementation (in months/years).
 - **ERP Background:**
 - Reasons for ERP adoption.
 - Customization level of the ERP system.
 - **Impact on BPR:**

- Perceived benefits of ERP on business processes (e.g., efficiency improvements, process standardization, data accuracy).
 - Overall satisfaction with ERP implementation and its impact on business processes.
- iv. **Data Collection Procedure:**
- **Pre-Survey Preparation:** Pilot the questionnaire with a small group of participants to refine questions and ensure clarity.
 - **Survey Distribution:** Send out the finalized questionnaire with a cover letter explaining the research objectives and ensuring confidentiality.
2. **Collaboration:** Collaboration with ERP vendors, consultants, and practitioners is crucial to ensure comprehensive data collection and context-specific policy formation. This collaboration will help tailor the machine learning algorithms to the unique needs of Sri Lankan organizations, enhancing the relevance and applicability of the research findings.
3. **Data Preprocessing:** The collected data will undergo rigorous preprocessing using the Python programming language to ensure accuracy and consistency:
- Data Cleaning: Handling missing values, outliers, and inconsistencies.
 - Data Transformation: Encoding categorical variables and scaling numerical features.
 - Data Integration: Merging data from different sources to create a unified dataset for analysis.
4. **Dataset Analysis Process:** The dataset analysis for assessing the impact of ERP system implementation on BPR follows a structured, multi-step process implemented through an interactive application. Initially, the dataset is uploaded in CSV format and loaded using pandas. Any issues with file reading are promptly communicated to the user. Upon successful upload, the user selects a target variable corresponding to specific indicators of ERP impact on business processes. These target variables include the overall impact of ERP implementation, the extent to which ERP streamlines business processes, and the level of agreement on ERP's role in achieving business process reengineering goals.

Based on the selected target, the system identifies a predefined set of relevant features reflecting critical factors such as ERP decision-making considerations, customization impacts, and top management roles. The presence of all required features is verified before proceeding. Data preprocessing involves addressing missing values by imputing the mode for categorical variables and the median for numerical ones. All categorical data are then converted into numerical format via label encoding to facilitate model training. Additionally, feature scaling is applied using standardization to normalize the data, which is essential for models sensitive to feature magnitude.

The preprocessed dataset is split into training and testing subsets, with proportions adjusted depending on the chosen model and target variable, ensuring reliable evaluation of model performance. Four machine learning models are available: Gaussian Naïve Bayes, Decision Tree, K-Nearest Neighbors, and Artificial Neural Networks. Each model is trained on the training set and evaluated on the test set. The Naïve Bayes classifier applies probabilistic reasoning with Gaussian assumptions, while the Decision Tree classifier constructs a tree with a controlled depth to avoid overfitting and includes visualization for interpretability. The KNN model performs hyperparameter tuning by testing various neighbor values to select the optimal K based on accuracy. The ANN model employs a feed-forward neural network with three hidden layers using ReLU activation and is trained over multiple epochs to capture complex nonlinear relationships.

Model evaluation encompasses multiple metrics: confusion matrices visually display the relationship between actual and predicted classes; accuracy scores quantify overall correctness; and classification reports provide precision, recall, and F1-scores for each class, offering a comprehensive understanding of model strengths and weaknesses. For the KNN model, additional plots of error rates and accuracy across different K values aid in selecting the best hyperparameters. This systematic and detailed analysis pipeline facilitates a robust assessment of ERP implementation's impact, leveraging various machine learning techniques to uncover influential factors and predict outcomes effectively.

5. **Model Building:** Machine learning algorithms will be used to construct a model for analyzing the impact of ERP implementation on business processes. This new model will be developed using the CRISP-DM model, which serves as a structured framework for coordinating the problem-solving strategy through data mining and achieving the objectives of BPR. This model encompasses 6 phases:
 - i. **Business Understanding:** defining the requirements and objectives from a business perspective in order to influence the problem definition.
 - ii. **Data Understanding:** Initial data collection and exploration to understand data characteristics and identify initial patterns.
 - iii. **Data Preparation:** Preparing the final dataset for modeling, including data cleaning, transformation, and integration.
 - iv. **Modeling:** Applying machine learning methods such as:
 - **Neural Networks:** For predictive analytics and identifying complex patterns.
 - **Decision Trees:** For classification and regression tasks to understand the decision-making process.
 - **KNN (K-Nearest Neighbors)**
 - **Naïve Bayes**
 - **GBM (Gradient Boosting Machine)**

- v. Evaluation: Evaluating the model's performance with metrics such as F1-score, recall, accuracy, and precision. Techniques for cross-validation will be used to make sure the models are reliable.

The CRISP-DM model provides a standardized view. To drive business innovation effectively, a balanced approach that integrates both business understanding and data mining expertise is essential. This integration may involve collaboration among various stakeholders, including IT experts, business experts, and data miners, each contributing their unique insights and knowledge.

The interaction between business processes, data mining, and machine learning is most prominent in the 'business understanding' and 'deployment' phases within the CRISP-DM framework. By incorporating the CRISP-DM process as a fundamental component of the model, this study aims to establish effective interaction between ERP implementation and business process reengineering, ensuring a comprehensive analysis of their impact and fostering successful integration within organizational processes [52].

6. **Testing and Validating the Model:** The dataset has been split into training and testing subsets during the data splitting stage. 30% is utilized for testing, while 70% is used for training. This is a crucial step in model development and evaluation:
 - Training Set: The model is trained using a portion of the data. The model learns from this data, identifying patterns and relationships that will enable it to make predictions based on input data.
 - Testing Set: The remaining data is used to test the model's performance. This set is not used during the training process, providing an unbiased evaluation of how well the model performs on new, unseen data.

The model was created using the training set, and its effectiveness was evaluated using the testing set. Evaluated the model's performance using accuracy, precision, recall, or mean squared error.

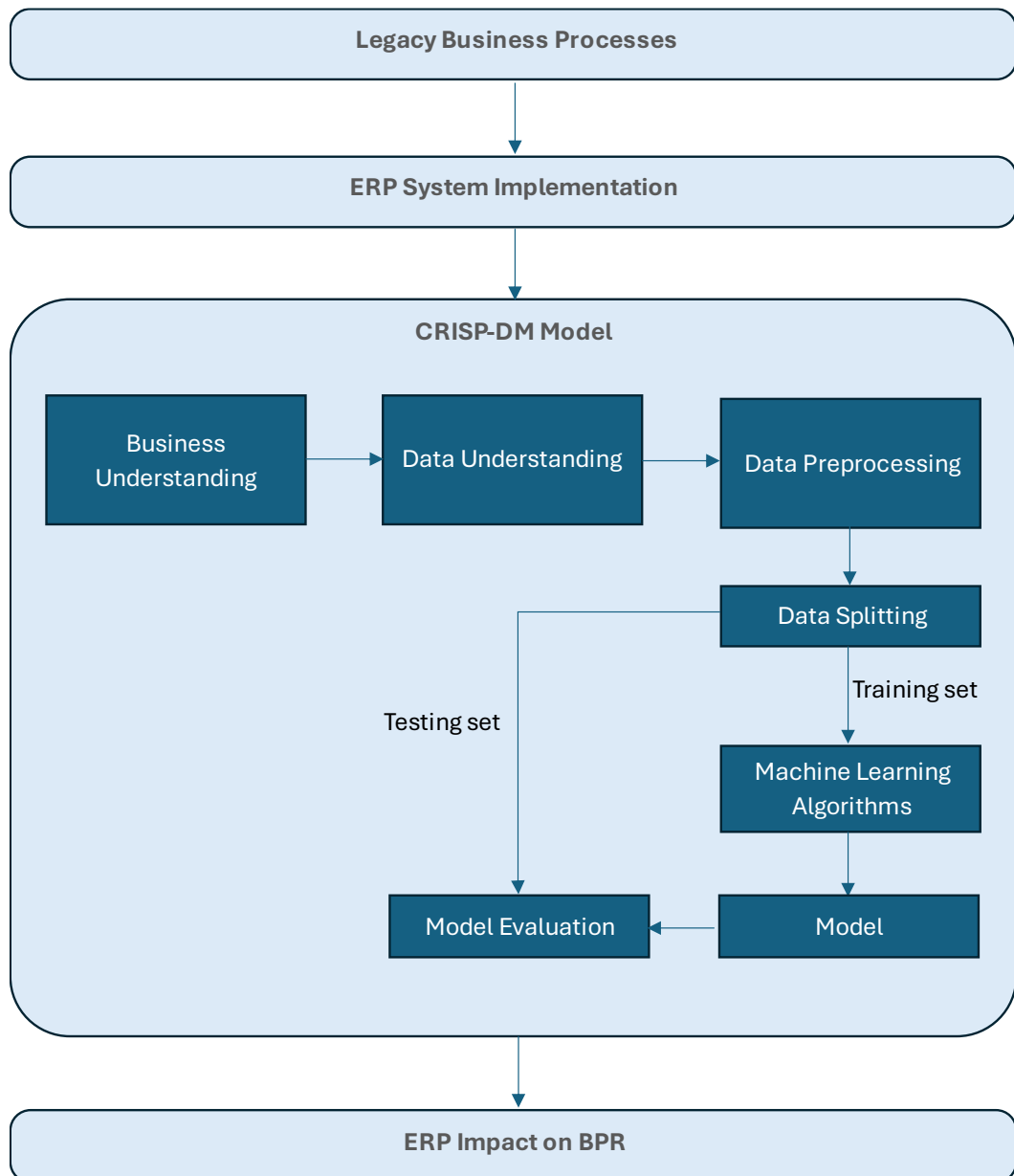


Figure 3-1: Framework of the proposed model

The proposed model framework, as depicted in Figure 3-1, illustrates the integration of legacy business processes, ERP system implementation, and the CRISP-DM model. This module encompasses several key phases, including Business Understanding, Data Understanding, Data Preprocessing, Data Splitting, and Model Evaluation.

The innovative approaches presented in this paper underscore the interconnection between the CRISP-DM model and BPR. It is crucial to emphasize that for optimal outcomes in applying data mining and machine learning to BPR, both approaches must be considered simultaneously. This holistic approach enables the identification, analysis, and enhancement of business processes, ultimately evaluating the impact of ERP implementation on various business processes.

3.3 Interpretation of Research Findings

The research findings reveal that ERP implementation has a significant positive impact on Business Process Reengineering (BPR) in Sri Lankan organizations, as evidenced by the strong performance of machine learning models in predicting satisfaction and agreement levels. Techniques such as Decision Trees, KNN, and Naive Bayes demonstrated high accuracy and reliability in identifying satisfied and strongly satisfied responses, indicating that ERP systems are effective in streamlining business processes and achieving BPR goals.

3.4 Conclusion and Recommendation

The research demonstrates that machine learning algorithms are effective tools for evaluating the impact of ERP implementation on BPR. The findings confirm that ERP systems play a crucial role in improving business processes, particularly in enhancing efficiency and achieving reengineering goals. The future research should explore advanced machine learning techniques, expand datasets to include diverse industries and regions, and incorporate qualitative insights to provide a more holistic understanding of ERP's impact on BPR. These recommendations aim to enhance the effectiveness of ERP systems and support organizations in achieving their business process reengineering objectives.

CHAPTER 4

IMPLEMENTATION

4.1 Introduction

Chapter 4 outlines the high-level design related to the three research objectives concerning the Machine Learning-Based Impact Assessment of ERP System Implementation in Business Process Re-engineering. This chapter discusses the implementation of each research question in terms of the methods used. Additionally, it presents the implementation of the proposed solution, including the system architecture and high-level design, supported by a diagram.

4.2 High-Level Architecture of the Proposed Model Prototype

The proposed model prototype is built using a three-tier architecture, consisting of three primary modules: User Interface, Model Processing, and a Database for Storing User Inputs. This layered design enables separation of concerns, improves system scalability, and enhances maintainability.

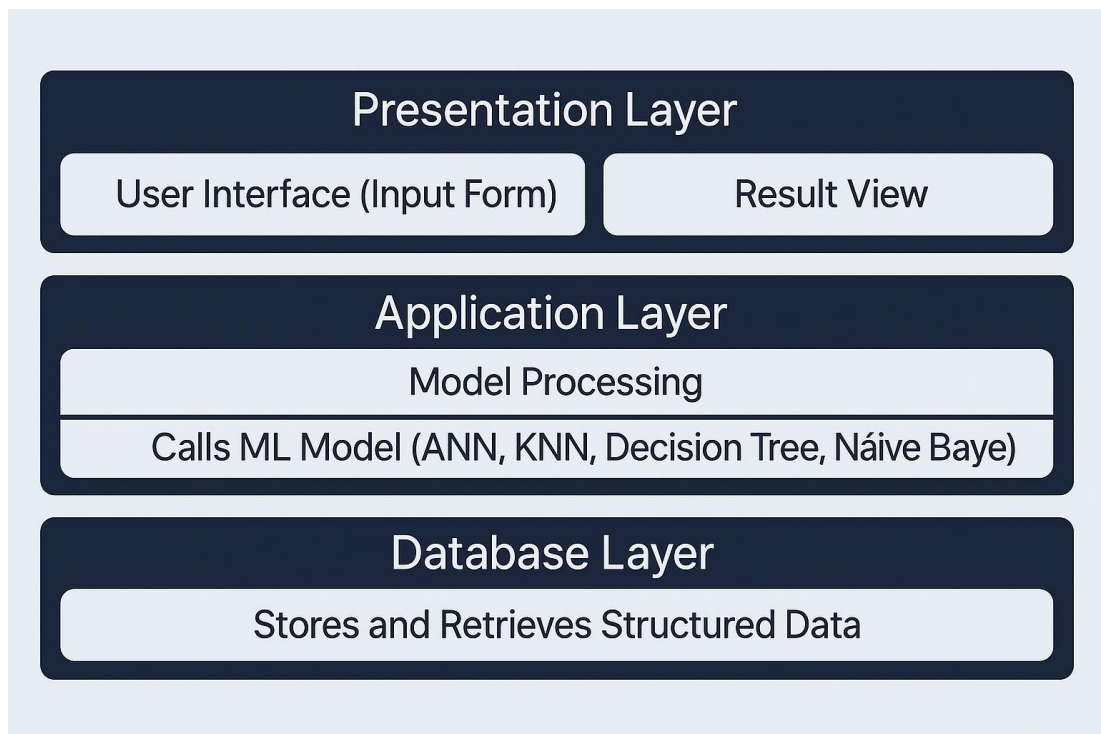


Figure 4-1: Diagram for Machine Learning-Based Impact Assessment of ERP System Implementation in the BPR Tool

Presentation Layer: This top layer serves as the point of interaction between the user and the system. It includes input forms where users can provide relevant data for analysis, such as ERP-related factors or satisfaction levels. Once the machine learning model completes processing, the results are displayed on the same interface for user interpretation.

Application Layer: The core logic of the system resides in this middle layer. It handles all computational operations, including data preprocessing and the execution of machine learning models. The application layer dynamically calls one of the predefined models, such as Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), Decision Tree, or Naïve Bayes, based on user selection or system configuration. This layer ensures smooth integration of machine learning workflows for ERP impact assessment in Business Process Reengineering (BPR).

Database Layer: The bottom layer is responsible for storing and retrieving structured data. It holds user inputs, processed results, and possibly model training data. This persistent storage enables the system to maintain a history of analysis and support future references or batch processing needs.

4.3 User Interfaces of the Tool

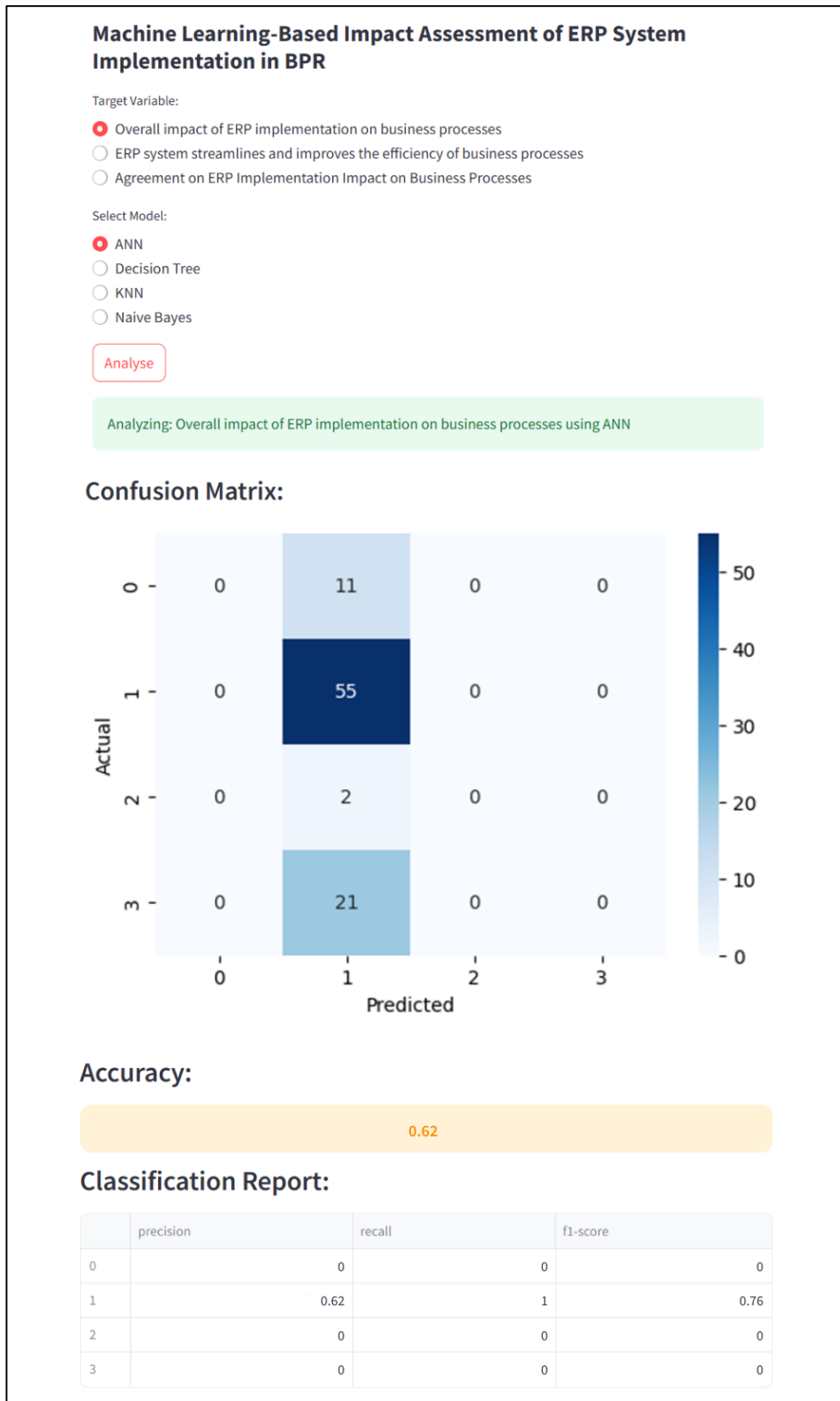


Figure 4-2: User Interface - ANN - Overall impact of ERP implementation on business processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

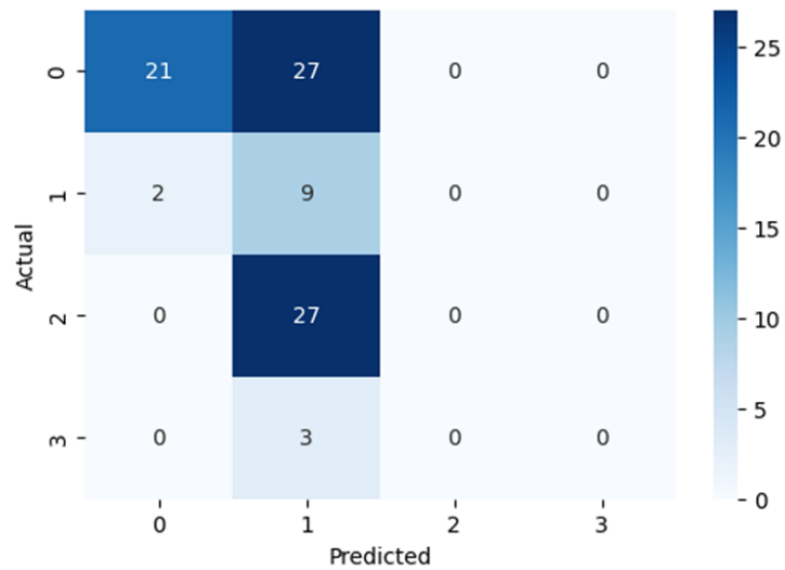
Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: ERP system streamlines and improves the efficiency of business processes using ANN

Confusion Matrix:



Accuracy:

0.34

Classification Report:

	precision	recall	f1-score
0	0.91	0.44	0.59
1	0.14	0.82	0.23
2	0	0	0
3	0	0	0

Figure 4-3: User Interface - ANN - ERP system streamlines and improves the efficiency of business processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

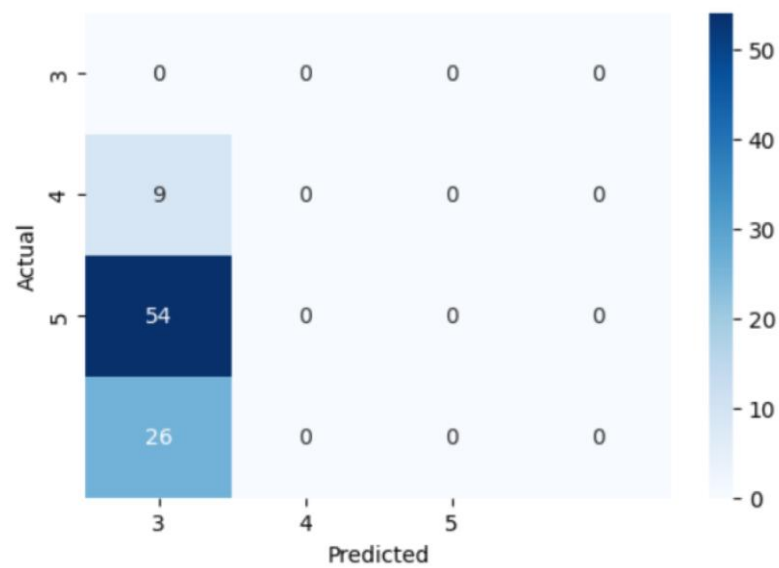
Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: Agreement on ERP Implementation Impact on Business Processes using ANN

Confusion Matrix:



Accuracy:

0.00

Classification Report:

	precision	recall	f1-score
1	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0

Figure 4-4: User Interface - ANN - Agreement on ERP Implementation Impact on Business Processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

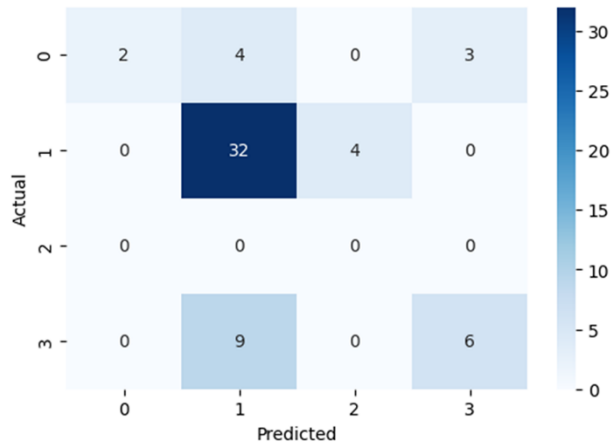
Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: Overall impact of ERP implementation on business processes using Decision Tree

Confusion Matrix:



Decision Tree Visualization:



Accuracy:

0.67

Classification Report:

	precision	recall	f1-score	
0		1	0.22	0.36
1		0.71	0.89	0.79
2		0	0	0
3		0.67	0.40	0.50

Figure 4-5: User Interface - Decision Trees - Overall impact of ERP implementation on business processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

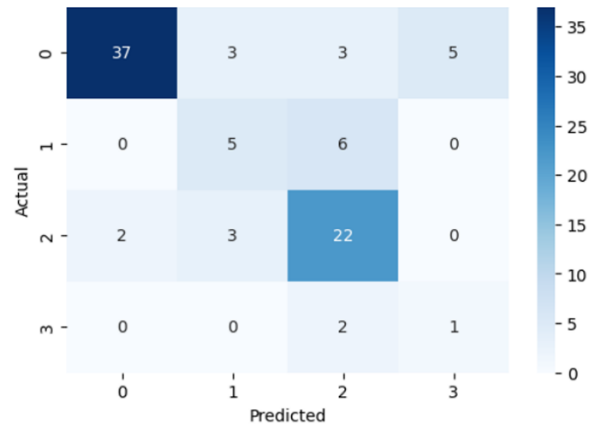
Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: ERP system streamlines and improves the efficiency of business processes using Decision Tree

Confusion Matrix:



Decision Tree Visualization:



Accuracy:

0.73

Classification Report:

	precision	recall	f1-score	
0		0.95	0.77	0.85
1		0.45	0.45	0.45
2		0.67	0.81	0.73
3		0.17	0.33	0.22

Figure 4-6: User Interface - Decision Trees - ERP system streamlines and improves the efficiency of business processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

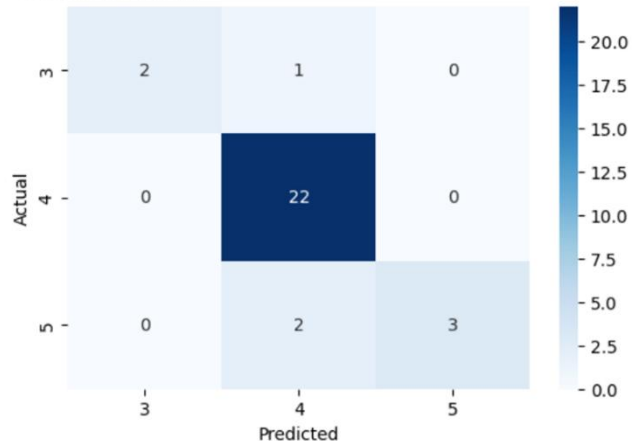
Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

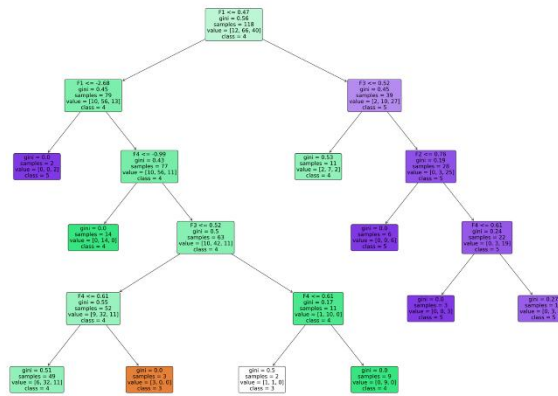
Analyse

Analyzing: Agreement on ERP Implementation Impact on Business Processes using Decision Tree

Confusion Matrix:



Decision Tree Visualization:



Accuracy:

0.90

Classification Report:

	precision	recall	f1-score	
3		1	0.67	0.80
4		0.88	1	0.94
5		1	0.60	0.75

Figure 4-7: User Interface - Decision Trees - Agreement on ERP Implementation Impact on Business Processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

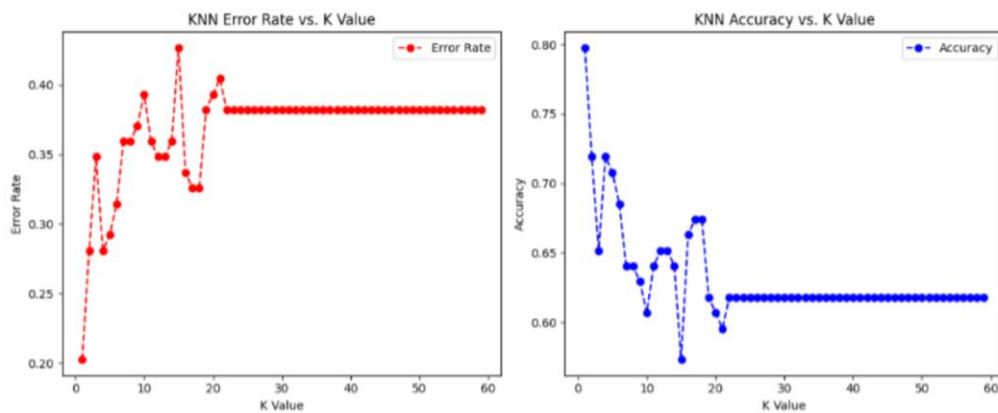
- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: Overall impact of ERP implementation on business processes using KNN



Accuracy:

0.80

Classification Report:

	precision	recall	f1-score
0	1	0.45	0.62
1	0.85	0.95	0.90
2	0.18	1	0.31
3	1	0.57	0.73

Figure 4-8: User Interface - KNN - Overall impact of ERP implementation on business processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

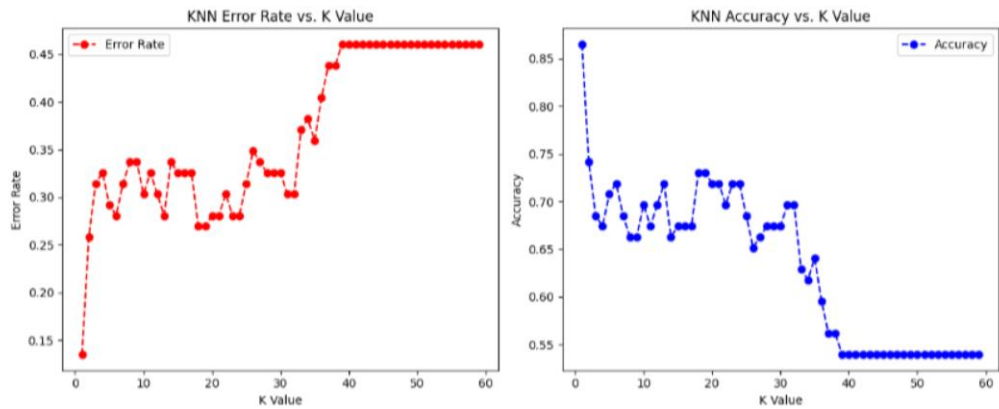
- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: ERP system streamlines and improves the efficiency of business processes using KNN



Accuracy:

0.87

Classification Report:

	precision	recall	f1-score
0	0.94	0.94	0.94
1	1	0.73	0.84
2	1	0.78	0.88
3	0.25	1	0.40

Figure 4-9: User Interface - KNN - ERP system streamlines and improves the efficiency of business processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

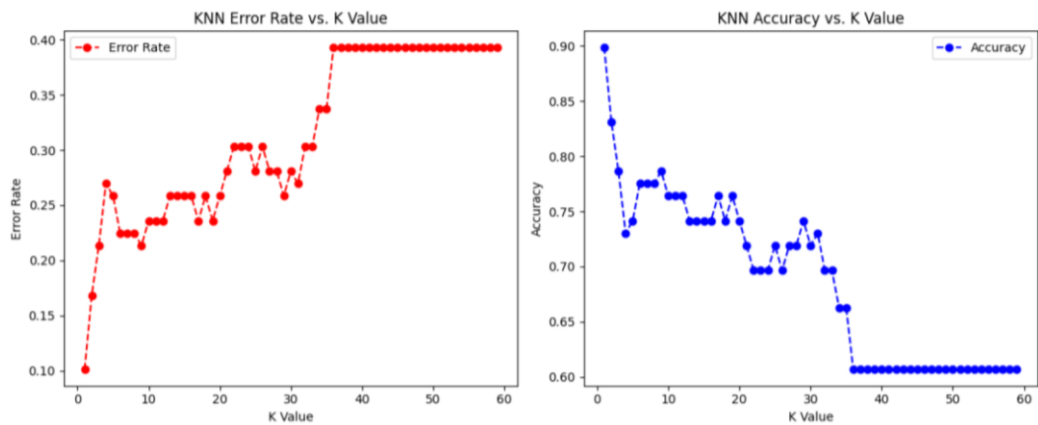
- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: Agreement on ERP Implementation Impact on Business Processes using KNN



Accuracy:

0.90

Classification Report:

	precision	recall	f1-score
3	1	0.67	0.80
4	0.89	0.94	0.92
5	0.88	0.88	0.88

Figure 4-10: User Interface - KNN - Agreement on ERP Implementation Impact on Business Processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

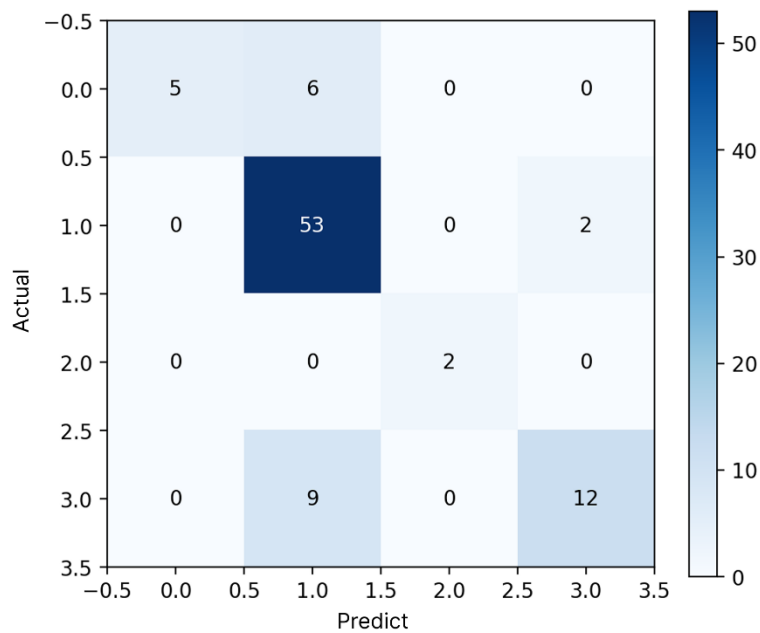
Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: Overall impact of ERP implementation on business processes using Naive Bayes

Confusion Matrix:



Accuracy:

0.81

Classification Report:

	precision	recall	f1-score
0	1	0.45	0.62
1	0.78	0.96	0.86
2	1	1	1
3	0.86	0.57	0.69

Figure 4-11: User Interface - Naïve Bayes - Overall impact of ERP implementation on business processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

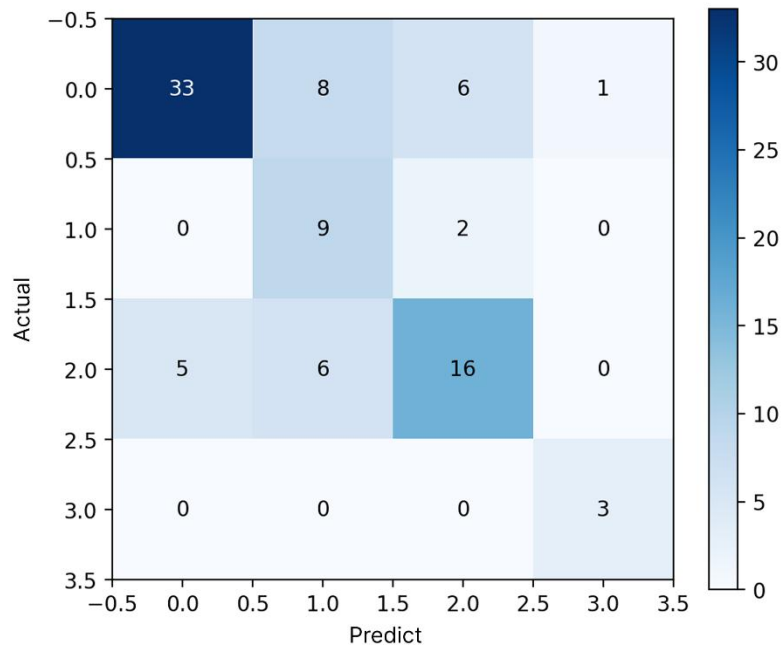
Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: ERP system streamlines and improves the efficiency of business processes using Naive Bayes

Confusion Matrix:



Accuracy:

0.69

Classification Report:

	precision	recall	f1-score
0	0.87	0.69	0.77
1	0.39	0.82	0.53
2	0.67	0.59	0.63
3	0.75	1	0.86

Figure 4-12: User Interface - Naïve Bayes - ERP system streamlines and improves the efficiency of business processes

Machine Learning-Based Impact Assessment of ERP System Implementation in BPR

Target Variable:

- Overall impact of ERP implementation on business processes
- ERP system streamlines and improves the efficiency of business processes
- Agreement on ERP Implementation Impact on Business Processes

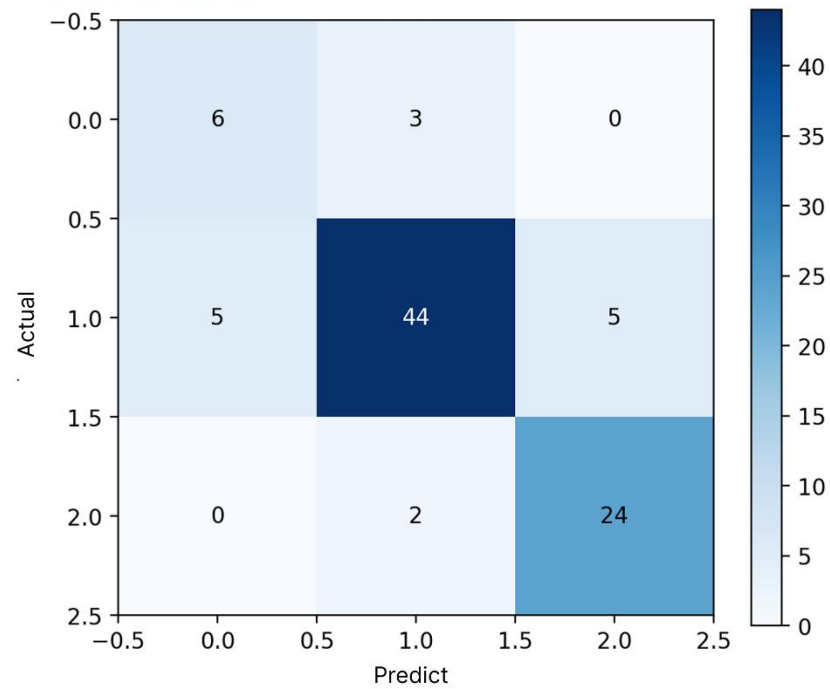
Select Model:

- ANN
- Decision Tree
- KNN
- Naive Bayes

Analyse

Analyzing: Agreement on ERP Implementation Impact on Business Processes using Naive Bayes

Confusion Matrix:



Accuracy:

0.83

Classification Report:

	precision	recall	f1-score	
3		0.55	0.67	0.60
4		0.90	0.81	0.85
5		0.83	0.92	0.87

Figure 4-13: User Interface - Naïve Bayes - Agreement on ERP Implementation Impact on Business Processes

4.4 Web-Based Tool

This prototype is a web-based tool that enables users to evaluate the impact of ERP implementation on business process re-engineering using machine learning techniques. Users can input business-related parameters, select a machine learning model, and receive predictions for three key impact metrics:

1. Overall impact of ERP implementation on business processes
2. ERP system streamlining and improving business process efficiency
3. Agreement on ERP Implementation Impact on Business Processes

4.5 Algorithms of the Proposed Model

4.5.1 ANN - Algorithm Design for ERP Impact Assessment in BPR

The Artificial Neural Network (ANN) models developed for analyzing the impact of ERP implementation across different dimensions follow a consistent methodological framework. The process begins with the importation of essential libraries, including pandas, numpy, matplotlib, seaborn, and relevant modules from scikit-learn and Keras for data manipulation, visualization, model construction, and evaluation. The dataset is loaded from a CSV file, and domain-specific features are selected based on the objective of each model. The target variable varies accordingly, capturing different aspects of perceived ERP impact on organizational processes.

Before moving forward, the script ensures that all selected features and the target variable are present in the dataset. If confirmed, preprocessing steps are applied, including the encoding of categorical variables using LabelEncoder to transform them into numerical format. The dataset is then split into training and testing sets using a 40/60 ratio. To normalize the feature scales and enhance neural network performance, input variables are standardized using the StandardScaler.

Using the ReLU activation function, the architecture starts with an input layer of 64 neurons. Two hidden layers with 32 and 16 neurons, respectively, are then added, both of which use ReLU activation. One neuron with a sigmoid activation function, appropriate for binary classification tasks, makes up the output layer. The Adam optimizer, binary cross-entropy as the loss function, and accuracy as the performance metric are used to create the model.

Training is carried out over 50 epochs with a batch size of 32, during which the model learns from the training data. Upon completion, predictions are made on the test data and converted to binary class labels using a threshold of 0.5. Model performance is then evaluated using accuracy, a confusion matrix, and a classification report. To visualize the predictive capability of the model, the confusion matrix is plotted as a heatmap, providing insights into classification outcomes relative to actual values.

4.5.2 Decision Tree - Algorithm Design for ERP Impact Assessment in BPR

The Decision Tree (DT) classification models designed to analyze ERP implementation outcomes begin with importing necessary libraries such as pandas, numpy, matplotlib, seaborn, and modules from scikit-learn for data processing, model training, and evaluation. After loading the dataset from a CSV file, relevant features are selected based on the specific focus of each model. The target variable varies accordingly and reflects the perceived impact or satisfaction with ERP implementation in the organization.

Prior to modeling, a validation step checks the presence of all selected features and the target variable within the dataset. If confirmed, data preprocessing is performed, including encoding categorical variables using LabelEncoder to convert them into numerical form. The dataset is then split into training and testing sets using a 40/60 ratio. Although scaling is optional for decision trees, StandardScaler is applied in these models to maintain consistency with other modeling approaches.

The Decision Tree model is constructed using the Gini index as the splitting criterion and a maximum depth of 5 to prevent overfitting while maintaining interpretability. The model is used to predict results on the test set after being trained on the training data. Evaluation metrics, including accuracy, confusion matrix, and a classification report, are computed to assess performance. These results are printed and visualized using a confusion matrix heatmap to provide a clearer understanding of prediction accuracy across actual and predicted classes. Lastly, the decision tree structure is graphically plotted to display the hierarchical flow of decision rules.

4.5.3 KNN - Algorithm Design for ERP Impact Assessment in BPR

The K-Nearest Neighbors (KNN) classification models used to assess ERP implementation impacts follow a structured process that begins with the importation of essential Python libraries, including pandas and numpy for data manipulation, matplotlib for visualization, and relevant modules from scikit-learn for preprocessing, model training, and evaluation. The dataset is loaded from a CSV file and inspected for missing values. These are addressed by filling numerical columns with their median values and categorical columns with their mode to ensure data consistency.

Categorical features are then transformed into numerical format using label encoding to make the data compatible with machine learning algorithms. The dataset is split into features (X) and a target variable (y), which varies depending on the research objectives. All input features are standardized using the StandardScaler to normalize the scale of numerical values, which is crucial for distance-based algorithms like KNN.

The data is then divided into training and testing sets using a 40/60 split ratio. To identify the most effective number of neighbors (K), the model iteratively evaluates multiple K values, calculating corresponding accuracy scores and error rates for each.

These results are visualized using line plots to assist in determining the optimal K value. Once identified, a final KNN classifier is trained using this optimal K and then tested on the reserved test set.

Model performance is evaluated using accuracy metrics and a classification report, which provides detailed insight into precision, recall, and F1-score for each class. This approach ensures that the selected K value is data-driven and optimally suited for the specific prediction task related to ERP implementation outcomes.

4.5.4 Naïve Bayes - Algorithm Design for ERP Impact Assessment in BPR

The Naïve Bayes (NB) classification models employed to predict ERP implementation outcomes follow a systematic approach starting with the importation of essential libraries such as pandas, numpy, matplotlib, and key modules from scikit-learn for preprocessing, modeling, and performance evaluation. The dataset is loaded from a CSV file and is first assessed for missing values. In order to maintain data integrity, any missing entries are suitably handled by filling in numerical columns with their median and categorical columns with their mode.

Next, all categorical variables are encoded using label encoding to ensure that they can be processed numerically by the model. After defining the target variable, which differs depending on the specific research objective, the remaining columns are used as input features. To ensure consistent feature scaling and optimize model performance, the input data is standardized using the StandardScaler.

The dataset is then split into training and testing subsets, typically using a 40/60 ratio to provide the model with ample test data for validation. A Gaussian Naïve Bayes classifier is then trained on the training set, leveraging the assumption of feature independence under a normal distribution. After training, the model generates predictions on the test data.

Metrics including accuracy, a classification report that includes precision, recall, and F1-score, and a confusion matrix that shows the distribution of true vs predicted labels are used to assess the model's performance. The confusion matrix is visualized using a color-coded heatmap to provide an intuitive understanding of the classifier's prediction effectiveness. This method offers a simple yet powerful baseline for ERP-related classification tasks due to its efficiency and interpretability, especially when working with high-dimensional data.

4.6 Machine Learning Techniques for Model Prediction

4.6.1 ANN for Model Prediction

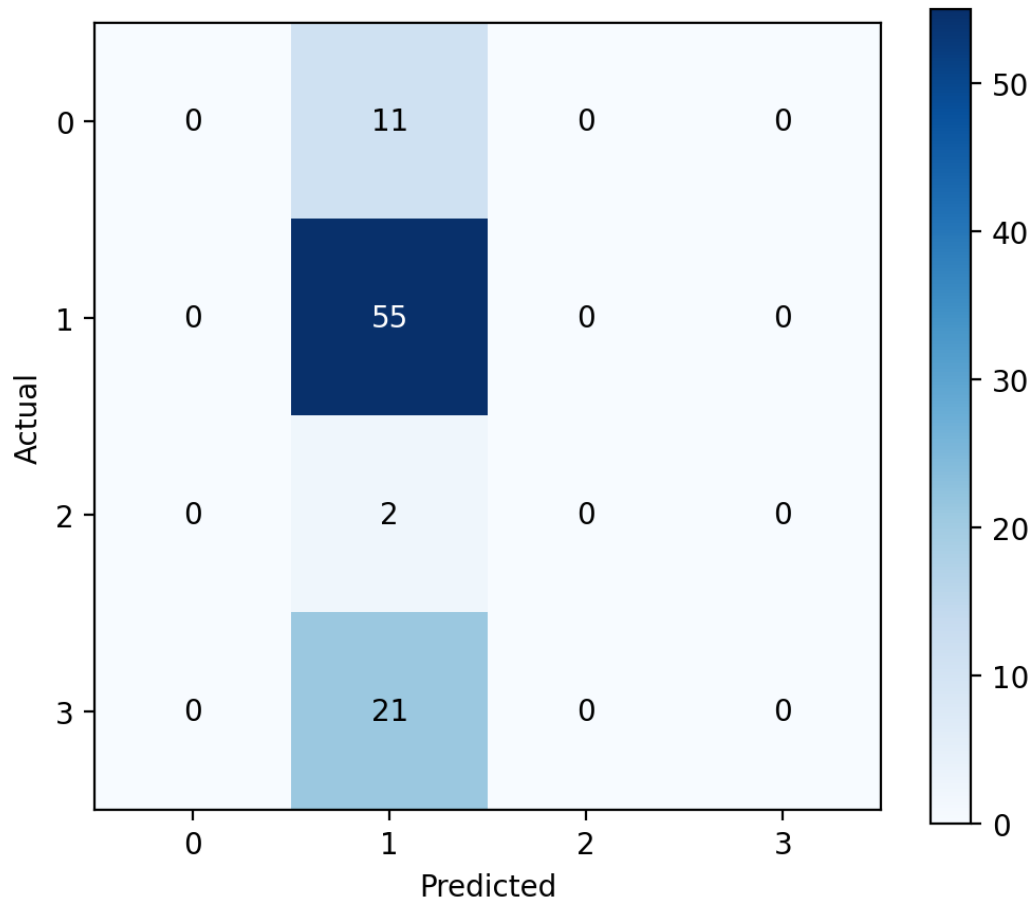


Figure 4-14: Confusion Matrix - ANN with model prediction based on overall impact of ERP implementation on business processes

The confusion matrix indicates that the ANN model demonstrates strong performance for Class 1, achieving 55 correct predictions with no misclassifications, which suggests effective separation for this class. For Class 0, all 11 instances are incorrectly predicted as Class 1. Similarly, for Class 2, both instances are misclassified as Class 1, and for Class 3, all 21 instances are also misclassified as Class 1.

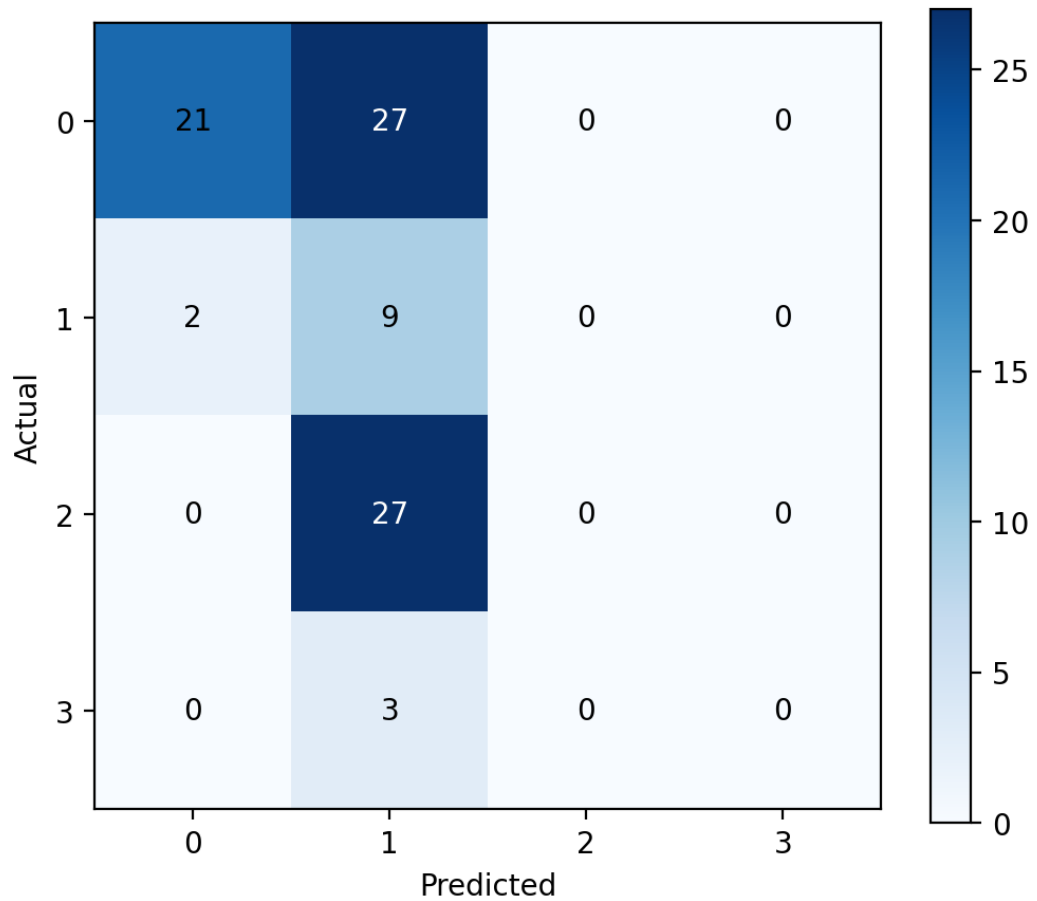


Figure 4-15: Confusion Matrix - ANN with model prediction based on ERP system streamlines and improves the efficiency of business processes

The confusion matrix reveals that the ANN model achieves 21 correct predictions for Class 0, though it misclassifies 27 instances as Class 1. For Class 1, the model correctly predicts 9 instances but misclassifies 2 as Class 0. Class 2 shows no correct predictions, with all 27 instances misclassified as Class 1. Similarly, Class 3 has no correct predictions, with all 3 instances misclassified as Class 1.

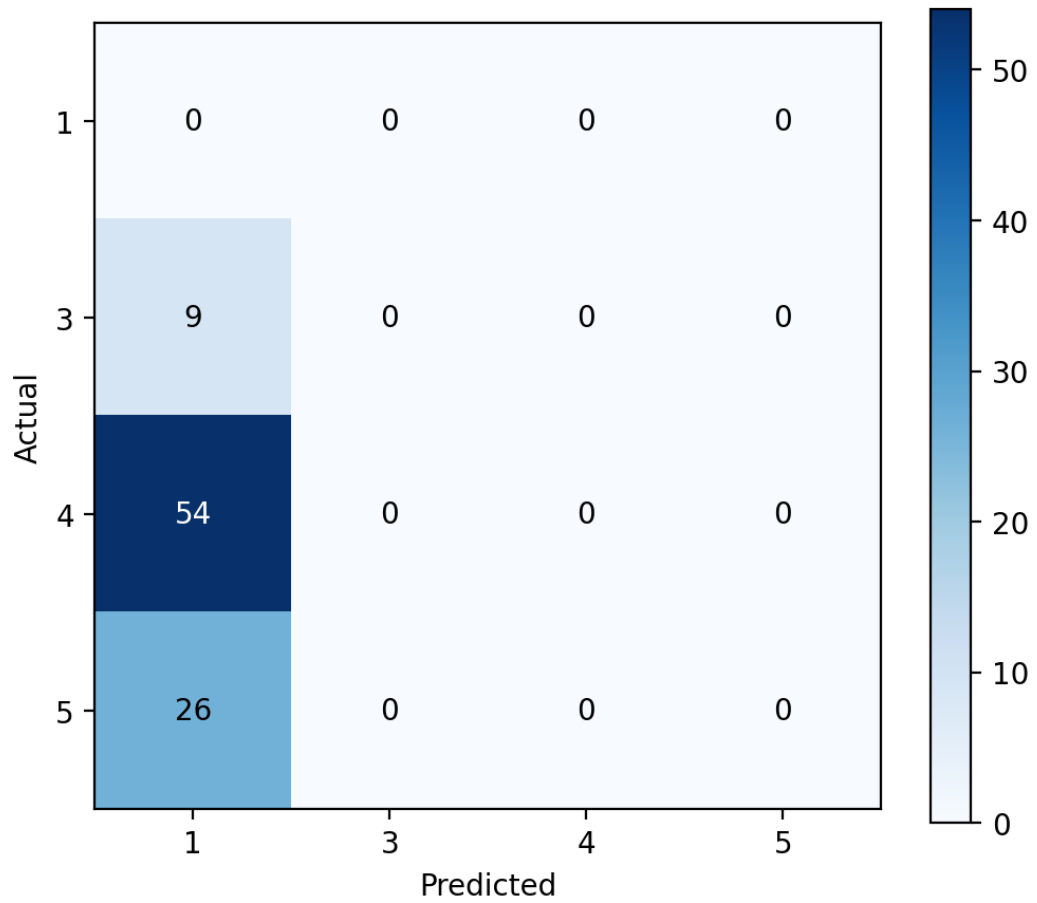


Figure 4-16: Confusion Matrix - ANN with model prediction based on Agreement on ERP Implementation Impact on Business Processes

The confusion matrix indicates that the ANN model fails to make any correct predictions across all classes. For Class 0, all instances are misclassified, with no correct predictions. Similarly, for Class 1, all 9 instances are misclassified, as are all 54 instances of Class 2 and all 26 instances of Class 3.

4.6.2 Decision Tree for Model Prediction

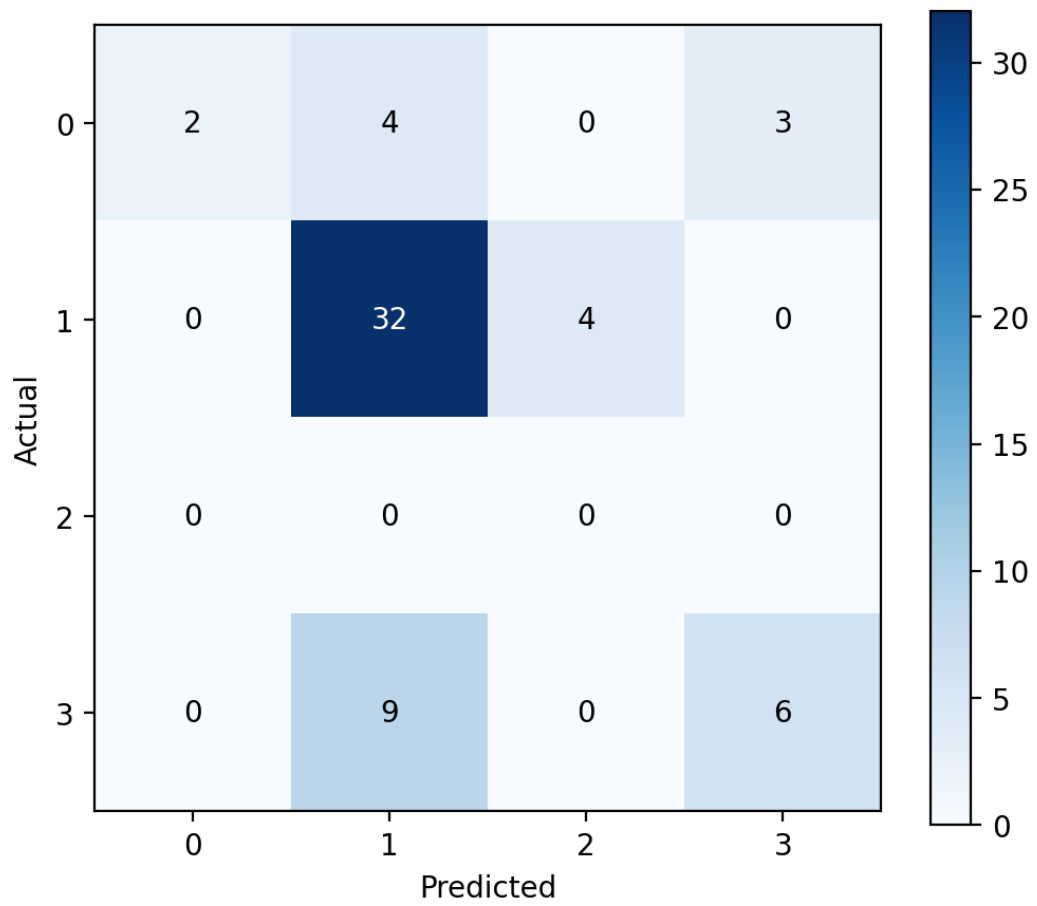


Figure 4-17: Confusion Matrix - Decision Tree with model prediction based on overall impact of ERP implementation on business processes



Figure 4-18: Decision Tree with model prediction based on overall impact of ERP implementation on business processes

The confusion matrix reveals that the Decision Tree model achieves 32 correct predictions for Class 1, though it misclassifies 4 instances as Class 2. For Class 0, the model correctly predicts 2 instances but misclassifies 4 as Class 1 and 3 as Class 3. Class 2 shows no correct predictions, with all instances misclassified, and Class 3 achieves 6 correct predictions but misclassifies 9 instances as Class 1.

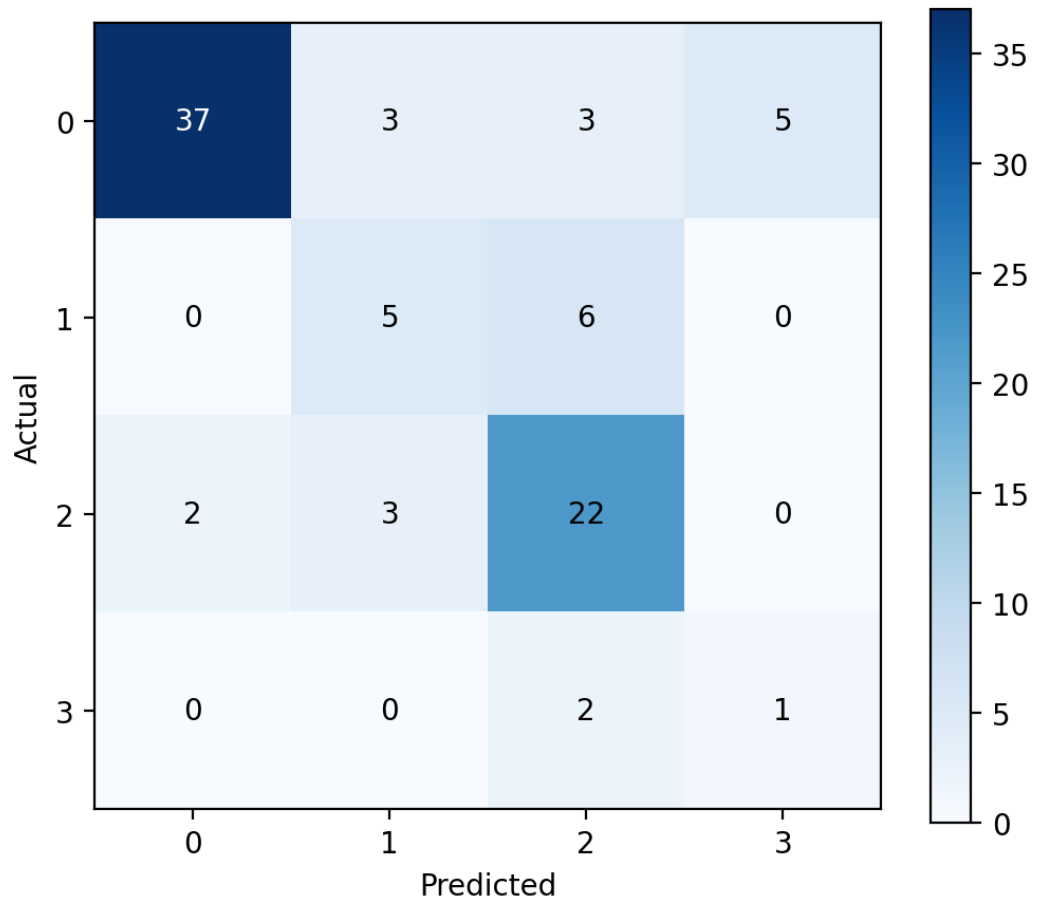


Figure 4-19: Confusion Matrix - Decision Tree with model prediction based on ERP system streamlines and improves the efficiency of business processes



Figure 4-20: Decision Tree with model prediction based on ERP system streamlines and improves the efficiency of business processes

The confusion matrix indicates that the Decision Tree model achieves 37 correct predictions for Class 0, though it misclassifies 3 instances as Class 1, 3 as Class 2, and 5 as Class 3. For Class 1, the model correctly predicts 5 instances but misclassifies 6 as Class 2. Class 2 shows 22 correct predictions, with 2 misclassified as Class 0 and 3 as Class 1. Class 3 achieves only 1 correct prediction, with 2 instances misclassified as Class 2. This pattern demonstrates varying performance across classes, with Class 0 and Class 2 showing relatively better accuracy, while Class 1 and Class 3 face limitations in correct classification. The matrix highlights the model's partial effectiveness in distinguishing between certain classes.

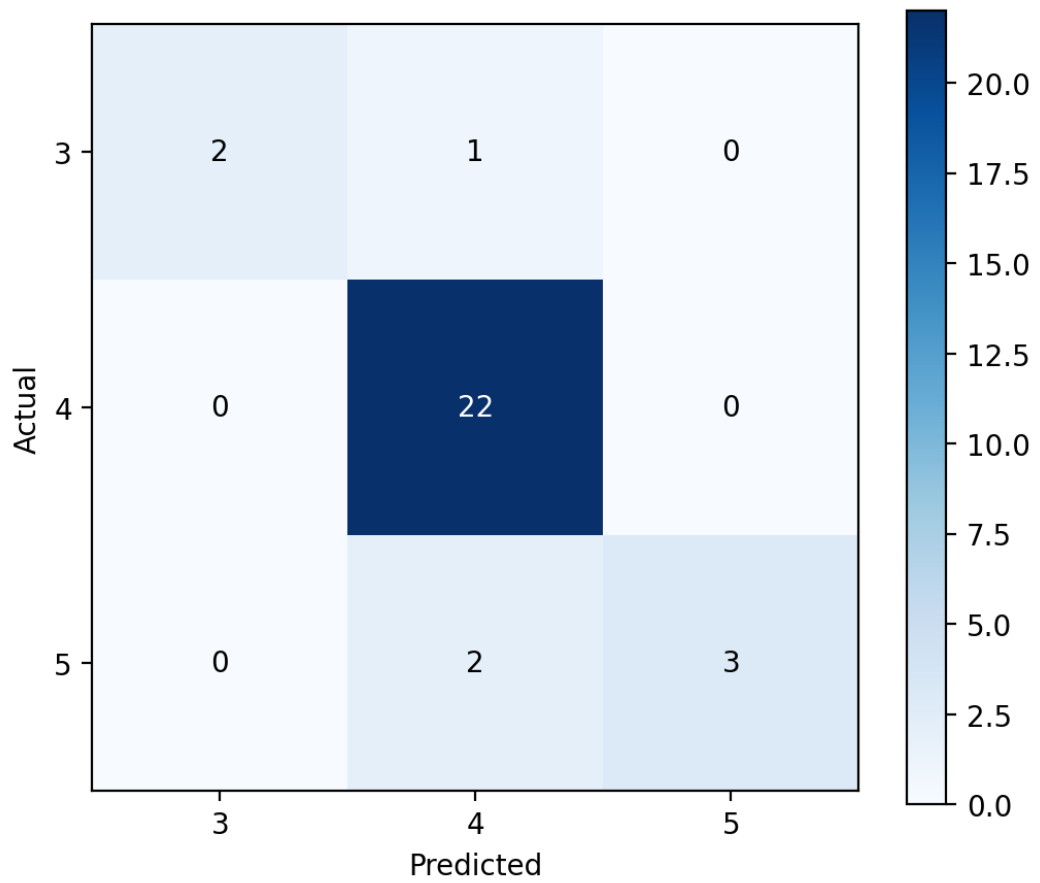


Figure 4-21: Confusion Matrix - Decision Tree with model prediction based on Agreement on ERP Implementation Impact on Business Processes

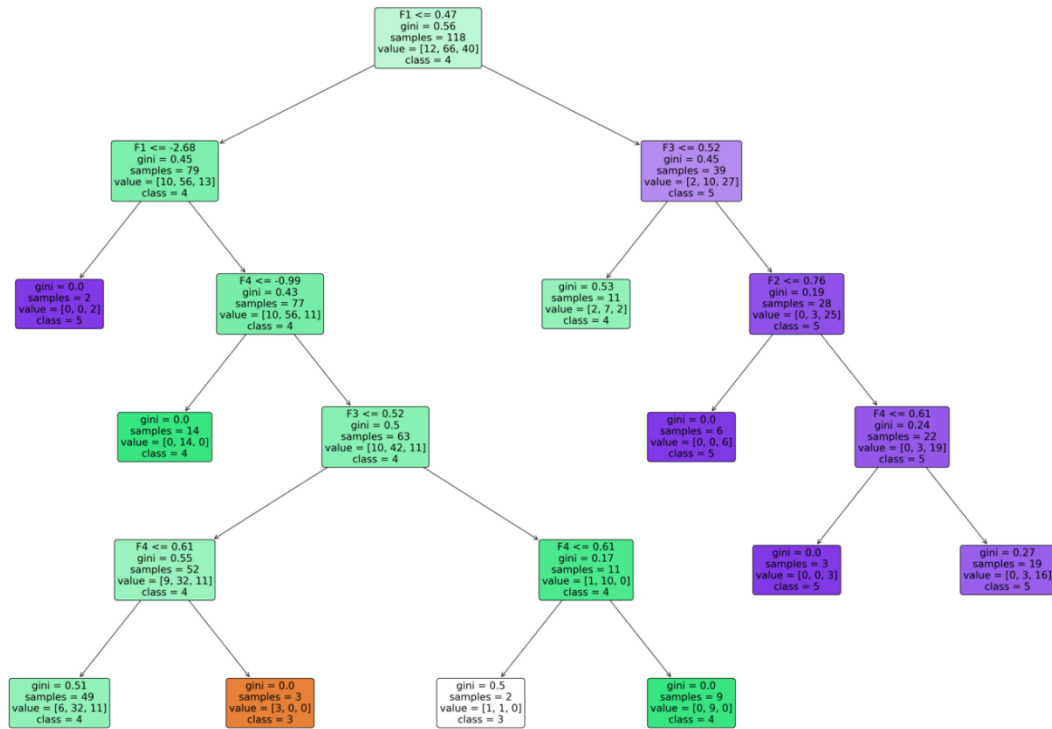


Figure 4-22: Decision Tree with model prediction based on Agreement on ERP Implementation Impact on Business Processes

The confusion matrix indicates that the Decision Tree model achieves 22 correct predictions for Class 1, with no misclassifications for this class. For Class 0, the model correctly predicts 2 instances but misclassifies 1 as Class 1. Class 2 shows 3 correct predictions, with 2 instances misclassified as Class 1. This pattern demonstrates strong performance for Class 1, while Class 0 and Class 2 exhibit partial accuracy with some misclassifications. The matrix highlights the model's effectiveness in classifying Class 1 but reveals limitations in achieving consistent accuracy across all classes, particularly for Class 0 and Class 2.

4.6.3 KNN for Model Prediction

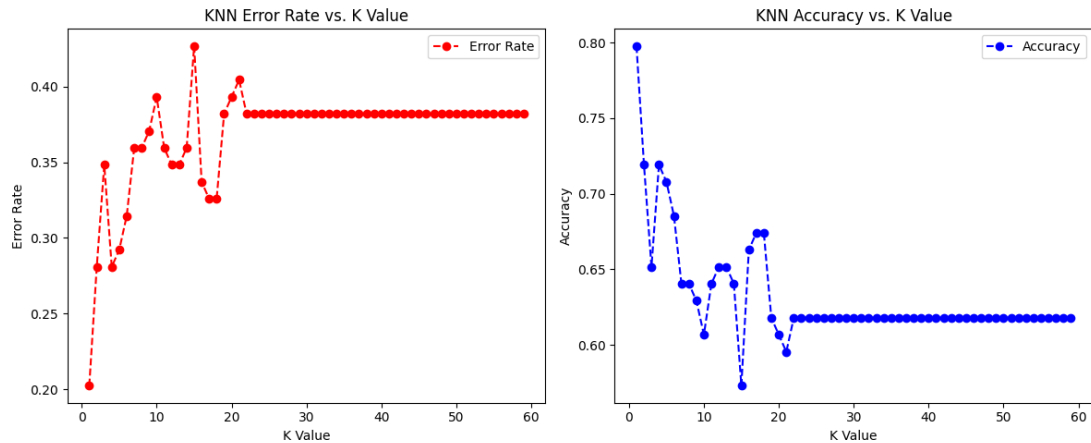


Figure 4-23: Graph - KNN with model prediction based on overall impact of ERP implementation on business processes

KNN Error Rate vs. K Values Graph:

The KNN Error Rate vs. K Values graph shows how the error rate changes as the value of K (number of neighbors) varies. With the optimal K value identified as 1, the model achieves an accuracy of 0.80, corresponding to an error rate of 0.20. At K=1, the error rate is minimized because the model relies on the closest neighbor, which tends to provide the most relevant information for classification. As K increases, the error rate generally rises because the inclusion of more distant neighbors can introduce noise and reduce the model's precision, particularly for classes with fewer samples, such as Class 2, which has a low precision of 0.18. The graph would depict a sharp increase in error rate as K moves away from 1, underscoring the importance of selecting the optimal K value to maintain low error rates.

KNN Accuracy vs. K Values Graph:

The KNN Accuracy vs. K Values graph illustrates how the model's accuracy changes with different values of K. At K=1, the model achieves its highest accuracy of 0.80, as indicated by the classification report. This accuracy is driven by strong performance for Class 1, which has high precision (0.85) and recall (0.95), and Class 3, which has perfect precision (1.00) but moderate recall (0.57). However, as K increases, the accuracy tends to decline because the model incorporates more neighbors, which can dilute the influence of the closest and most relevant data points, particularly affecting classes with fewer samples like Class 2.

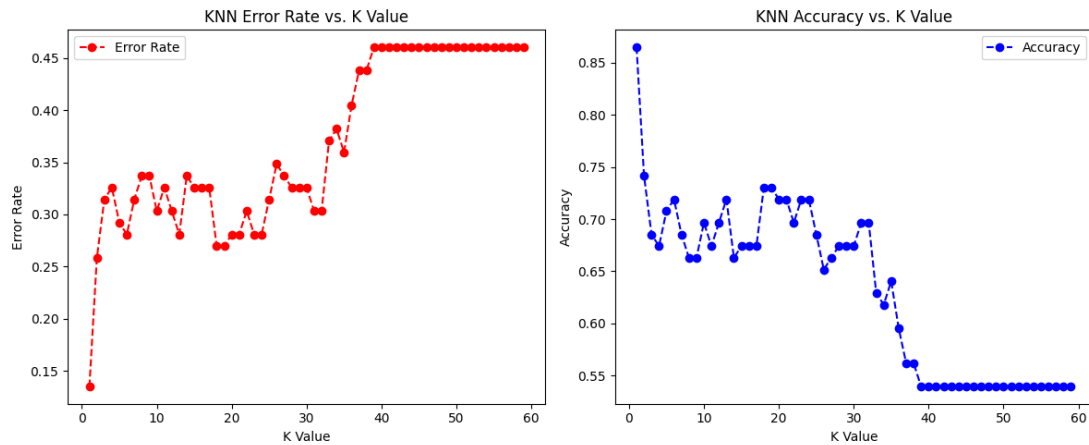


Figure 4-24: Graph - KNN with model prediction based on ERP system streamlines and improves the efficiency of business processes

KNN Error Rate vs. K Values Graph:

The KNN Error Rate vs. K Values graph illustrates how the error rate changes as the value of K (number of neighbors) varies. In this case, the optimal K value is identified as 1, which corresponds to the lowest error rate. When K=1, the model achieves an accuracy of 0.87, indicating a relatively low error rate of 0.13. As K increases beyond 1, the error rate typically rises due to the inclusion of more distant neighbors, which may introduce noise and reduce the model's ability to accurately classify instances. The graph would show a sharp increase in error rate as K moves away from 1, highlighting the sensitivity of the model to the choice of K and the importance of selecting the optimal value to minimize errors.

KNN Accuracy vs. K Values Graph:

The KNN Accuracy vs. K Values graph demonstrates how the model's accuracy changes with different values of K. At K=1, the model achieves its highest accuracy of 0.87, as indicated by the classification report. This high accuracy is driven by strong performance for Classes 0, 1, and 2, with precision and recall values close to or at 1.00 for these classes. However, as K increases, the accuracy tends to decline because the model incorporates more neighbors, which can dilute the influence of the closest and most relevant data points.

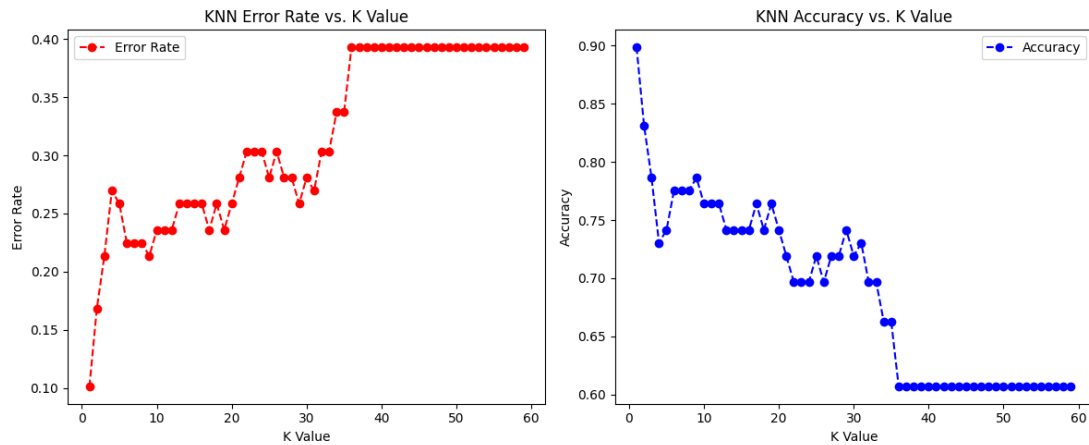


Figure 4-25: Graph - KNN with model prediction based on Agreement on ERP Implementation Impact on Business Processes

KNN Error Rate vs. K Values Graph:

The KNN Error Rate vs. K Values graph illustrates how the error rate changes as the value of K (number of neighbors) varies. With the optimal K value identified as 1, the model achieves an accuracy of 0.90, corresponding to an error rate of 0.10. At K=1, the error rate is minimized because the model relies on the closest neighbor, which tends to provide the most relevant information for classification. As K increases, the error rate generally rises because the inclusion of more distant neighbors can introduce noise and reduce the model's precision, particularly for classes with fewer samples, such as Class 3, which has a recall of 0.67. The graph would depict a sharp increase in error rate as K moves away from 1, underscoring the importance of selecting the optimal K value to maintain low error rates.

KNN Accuracy vs. K Values Graph:

The KNN Accuracy vs. K Values graph demonstrates how the model's accuracy changes with different values of K. At K=1, the model achieves its highest accuracy of 0.90, as indicated by the classification report. This accuracy is driven by strong performance for Class 4, which has high precision (0.89) and recall (0.94), and Class 5, which also shows balanced precision and recall (0.88 each). However, as K increases, the accuracy tends to decline because the model incorporates more neighbors, which can dilute the influence of the closest and most relevant data points, particularly affecting classes with fewer samples like Class 3.

4.6.4 Naïve Bayes for Model Prediction

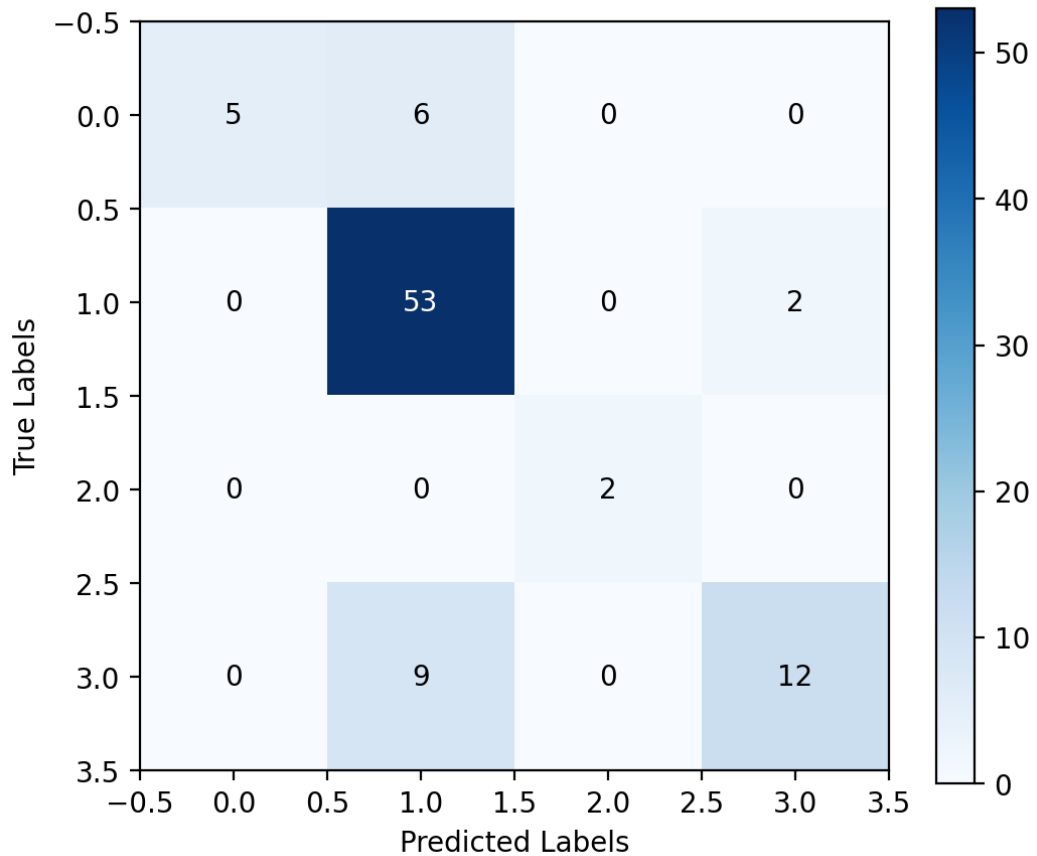


Figure 4-26: Confusion Matrix - Naive Bayes with model prediction based on overall impact of ERP implementation on business processes

The matrix indicates that the model performs well for Class 1, with 53 correct predictions, though it misclassifies 2 instances as Class 3. For Class 0, the model correctly predicts 5 instances but misclassifies 6 as Class 1. Class 2 has 2 correct predictions with no misclassifications, indicating good separation for this class. Class 3 shows 12 correct predictions, but 9 instances are misclassified as Class 1, highlighting potential confusion between these classes. Overall, the model performs best for Class 1.

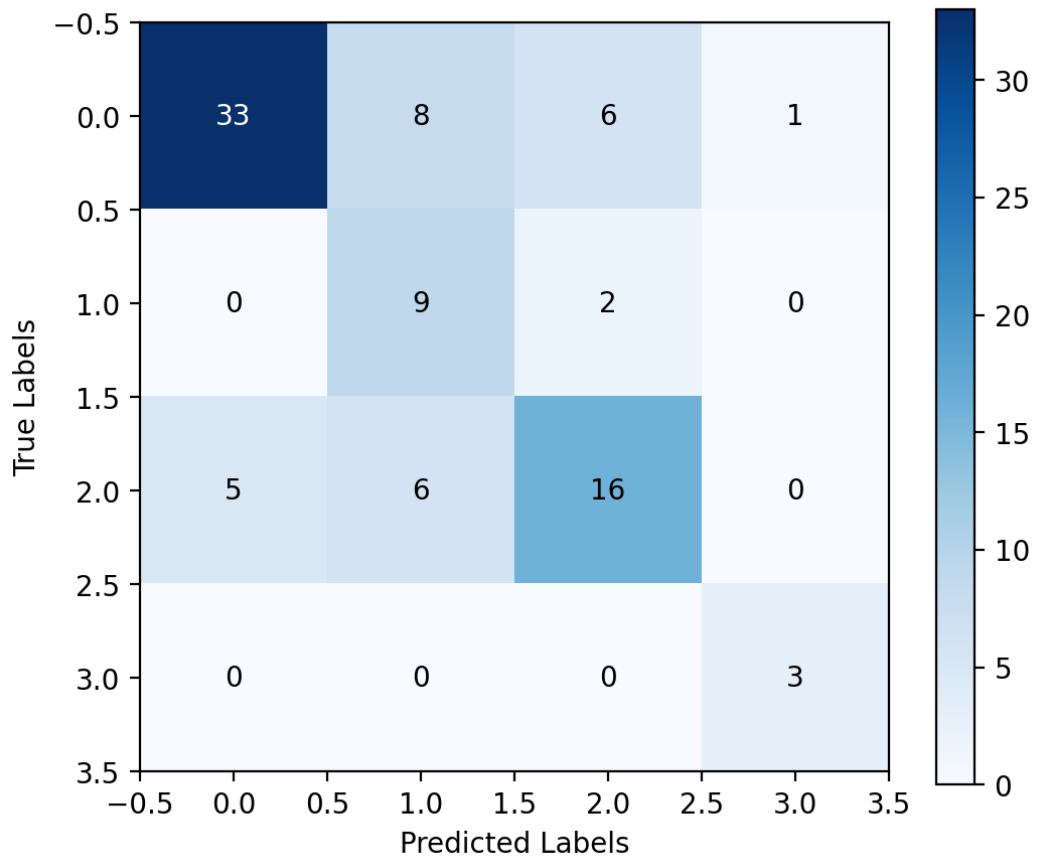


Figure 4-27: Confusion Matrix - Naive Bayes with model prediction based on ERP system streamlines and improves the efficiency of business processes

The matrix shows that the model performs reasonably well for Class 0, with 33 correct predictions, though it misclassifies 8 instances as Class 1, 6 as Class 2, and 1 as Class 3. For Class 1, the model correctly predicts 9 instances but misclassifies 2 as Class 2. Class 2 has 16 correct predictions, with 5 misclassified as Class 0 and 6 as Class 1. Class 3 has only 3 correct predictions with no misclassifications. Overall, the model demonstrates better performance for Class 0 and Class 2.

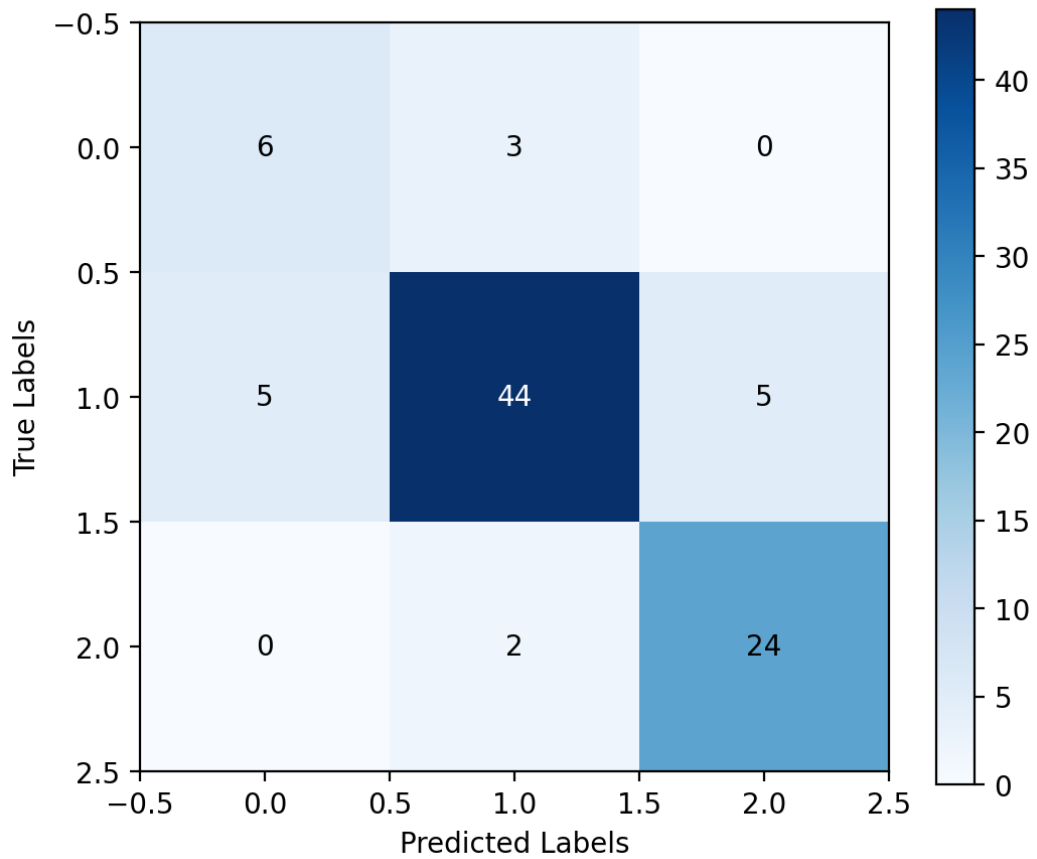


Figure 4-28: Confusion Matrix - Naive Bayes with model prediction based on Agreement on ERP Implementation Impact on Business Processes

The matrix indicates that the model performs well for Class 1, with 44 correct predictions, though it misclassifies 5 instances as Class 0 and 5 as Class 2, suggesting some overlap with these classes. For Class 0, the model correctly predicts 6 instances but misclassifies 3 as Class 1. Class 2 shows strong performance with 24 correct predictions, though 2 instances are misclassified as Class 1. Overall, the model demonstrates good accuracy for Classes 1 and 2.

CHAPTER 5

RESULTS AND DISCUSSION

This chapter provides a comprehensive analysis of the machine learning models used to predict how ERP adoption will affect Business Process Reengineering (BPR) in Sri Lankan companies. This examines the performance of various algorithms, including Artificial Neural Networks (ANN), Decision Trees, K-Nearest Neighbors (KNN), and Naive Bayes, in classifying survey responses related to ERP satisfaction, efficiency improvements, and BPR goal achievement. By analyzing key metrics such as accuracy, precision, recall, and F1-score, this chapter provides insights into the effectiveness of each model in capturing the relationship between ERP systems and business process outcomes. The findings highlight the strengths and limitations of the models, offering a data-driven perspective on how ERP implementation influences BPR. This analysis serves as the foundation for understanding the practical implications of ERP systems and sets the stage for discussions on model refinement and future research directions.

5.1 Machine Learning Techniques for Model Evaluation

5.1.1 ANN for Model Evaluation

TABLE 5-1: ANN WITH MODEL PREDICTION BASED ON OVERALL IMPACT OF ERP IMPLEMENTATION ON BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
How satisfied are you with the overall impact of ERP implementation on business processes in your organization?	0	0.62	0.00	0.00	0.00
	1		0.62	1.00	0.76
	2		0.00	0.00	0.00
	3		0.00	0.00	0.00

The Artificial Neural Network (ANN) model evaluation for predicting the impact of ERP implementation on business processes demonstrated mixed performance across different classes. The model performed well for Class 1 (Satisfied), achieving high precision (1.00) and recall (0.76), indicating that most actual satisfied responses were correctly identified with minimal false positives. However, the model completely failed to classify Class 0 (Dissatisfied), Class 2 (Neutral), and Class 3 (Strongly Satisfied), as all three classes had precision and recall values of 0.00. This suggests that the model could not correctly identify any instances from these classes, leading to a high misclassification rate. The overall accuracy of 62% was largely driven by the correct classification of Class 1, while other classes suffered from significant false negatives and false positives. These results indicate that the ANN model is biased toward predicting satisfied responses while struggling to distinguish dissatisfied, neutral, and strongly satisfied categories.

TABLE 5-2: ANN WITH MODEL PREDICTION BASED ON ERP SYSTEM STREAMLINES AND IMPROVES THE EFFICIENCY OF BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
To what extent do you agree that the ERP system streamlines and improves the efficiency of business processes in your organization?	0	0.34	0.91	0.44	0.59
	1		0.14	0.82	0.23
	2		0.00	0.00	0.00
	3		0.00	0.00	0.00

The evaluation of the Artificial Neural Network (ANN) model for the target variable "To what extent do you agree that the ERP system streamlines and improves the efficiency of business processes in your organization?" shows varied results across the different classes. For Class 0 (Strongly Disagree), the model achieved a precision of 0.91, with a recall of 0.44, indicating that while the model correctly identified some instances of strong disagreement, there was still a significant number of false negatives. Class 1 (Somewhat Agree) showed lower performance, with a precision of 0.14 and recall of 0.82, suggesting a higher number of false negatives and false positives. For Class 2 (Neutral) and Class 3 (Strongly Agree), the model could not accurately classify any instances, resulting in precision and recall values of 0.00.

TABLE 5-3: ANN WITH MODEL PREDICTION BASED ON AGREEMENT ON ERP IMPLEMENTATION IMPACT ON BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
Agreement on ERP Implementation Impact on Business Processes [The ERP system has contributed to achieving our business process reengineering goals.]	1	0.00	0.00	0.00	0.00
	3		0.00	0.00	0.00
	4		0.00	0.00	0.00
	5		0.00	0.00	0.00

The evaluation of the ANN model for the target variable "Agreement on ERP Implementation Impact on Business Processes [The ERP system has contributed to achieving our business process reengineering goals.]" revealed very poor performance across all classes. For Class 1, Class 3, Class 4, and Class 5, the model recorded a

precision, recall, and F1-score of 0.00, indicating that the model was unable to classify any instances accurately for these categories.

5.1.2 Decision Tree for Model Evaluation

TABLE 5-4: DECISION TREE WITH MODEL PREDICTION BASED ON OVERALL IMPACT OF ERP IMPLEMENTATION ON BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
How satisfied are you with the overall impact of ERP implementation on business processes in your organization?	0	0.67	1.00	0.22	0.36
	1		0.71	0.89	0.79
	2		0.00	0.00	0.00
	3		0.67	0.40	0.50

The evaluation of the Decision Tree model for the target variable "How satisfied are you with the overall impact of ERP implementation on business processes in your organization?" showed mixed performance across the classes. For Class 0 (Dissatisfied), the model achieved an accuracy of 0.67 with a precision of 1.00 but a low recall of 0.22 and an F1-score of 0.36, indicating that while the model correctly identified some instances, it struggled with overall prediction. Class 1 (Satisfied) showed a higher performance with an accuracy of 0.71, precision of 0.89, and recall of 0.79, indicating a reasonably good prediction for this class. However, for Class 2 (Neutral), the model achieved 0.00 precision and recall, signifying poor classification of this category. For Class 3, the model recorded an accuracy of 0.67, precision of 0.40, recall of 0.50, and F1-score of 0.43, demonstrating moderate performance. Overall, the model partially assesses the satisfaction level with ERP implementation, suggesting that ERP may have an impact on business processes.

TABLE 5-5: DECISION TREE WITH MODEL PREDICTION BASED ON ERP SYSTEM STREAMLINES AND IMPROVES THE EFFICIENCY OF BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
To what extent do you agree that the ERP system streamlines and improves the efficiency of business processes in your organization?	0	0.73	0.95	0.77	0.85
	1		0.45	0.45	0.45
	2		0.67	0.81	0.73
	3		0.17	0.33	0.22

The Decision Tree model for the target variable "To what extent do you agree that the ERP system streamlines and improves the efficiency of business processes in your organization?" demonstrated varying degrees of performance across the classes. For Class 0 (Strongly disagree), the model performed well, achieving an accuracy of 0.73 with a precision of 0.95, recall of 0.77, and an F1-score of 0.85, indicating good prediction. For Class 1 (Somewhat agree), the model had lower performance with an accuracy of 0.45, precision, recall, and F1-score all at 0.45, indicating limited effectiveness in predicting this class. Class 2 (Agree) showed moderate performance with an accuracy of 0.67, precision of 0.81, and recall of 0.73. Lastly, for Class 3 (Strongly agree), the model achieved an accuracy of 0.17, with low precision (0.33), recall (0.22), and F1-score, suggesting weak classification. In conclusion, while the model indicates some level of impact of ERP implementation on streamlining business processes.

TABLE 5-6: DECISION TREE WITH MODEL PREDICTION BASED ON AGREEMENT ON ERP IMPLEMENTATION IMPACT ON BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
Agreement on ERP Implementation Impact on Business Processes [The ERP system has contributed to achieving our business process reengineering goals.]	3	0.90	1.00	0.67	0.80
	4		0.88	1.00	0.94
	5		1.00	0.60	0.75

The Decision Tree model for the target variable "Agreement on ERP Implementation Impact on Business Processes [The ERP system has contributed to achieving our business process reengineering goals.]" showed strong performance across the classes. For Class 3 (Agree), the model achieved an accuracy of 0.90, with a precision of 1.00, recall of 0.67, and an F1-score of 0.80, reflecting a high level of prediction accuracy. Class 4 (Strongly agree) also performed well with an accuracy of 0.88, precision of 1.00, and recall of 0.94, suggesting excellent prediction for this class. Class 5 (Completely agree) showed a slightly lower performance with an accuracy of 1.00, but with precision of 0.60 and recall of 0.75, indicating room for improvement in classifying this level of agreement. Overall, the model successfully indicates a positive impact of ERP implementation on achieving business process reengineering goals, especially for higher levels of agreement, suggesting that the ERP system has a notable effect on BPR.

5.1.3 KNN for Model Evaluation

TABLE 5-7: KNN WITH MODEL PREDICTION BASED ON OVERALL IMPACT OF ERP IMPLEMENTATION ON BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
How satisfied are you with the overall impact of ERP implementation on business processes in your organization?	0	0.80	1.00	0.45	0.62
	1		0.85	0.95	0.90
	2		0.18	1.00	0.31
	3		1.00	0.57	0.73

The KNN model for the target variable "How satisfied are you with the overall impact of ERP implementation on business processes in your organization?" performed effectively across several classes. For Class 0 (Dissatisfied), the model achieved an accuracy of 0.80, with a precision of 1.00, recall of 0.45, and an F1-score of 0.62, indicating a strong prediction for dissatisfaction but with room for improvement in recall. Class 1 (Satisfied) showed excellent results with an accuracy of 0.85, precision of 0.95, and recall of 0.90, reflecting the model's strong ability to predict satisfaction. Class 2 (Neutral) had lower performance with an accuracy of 0.18, precision of 1.00, but a recall of 0.31, suggesting that the model struggles to predict neutrality accurately. For Class 3 (Very satisfied), the accuracy was 1.00, with precision of 0.57 and recall of 0.73, indicating that while the model perfectly identifies this class. Overall, the model highlights that the ERP system's impact on business processes is perceived positively, especially among satisfied and very satisfied respondents, with a stronger correlation between ERP implementation and positive business process outcomes.

TABLE 5-8: KNN WITH MODEL PREDICTION BASED ON ERP SYSTEM STREAMLINES AND IMPROVES THE EFFICIENCY OF BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
To what extent do you agree that the ERP system streamlines and improves the efficiency of business processes in your organization?	0	0.87	0.94	0.94	0.94
	1		1.00	0.73	0.84
	2		1.00	0.78	0.88
	3		0.25	1.00	0.40

The KNN model for the target variable "To what extent do you agree that the ERP system streamlines and improves the efficiency of business processes in your organization?" performed effectively across several classes. For Class 0 (Strongly agree), the model achieved an accuracy of 0.87, with a precision of 0.94, recall of 0.94, and an F1-score of 0.94, indicating a strong prediction for strong agreement. Class 1 (Agree) showed excellent results with an accuracy of 0.87, precision of 1.00, and recall of 0.73, reflecting the model's strong ability to predict agreement. Class 2 (Neutral) had lower performance with an accuracy of 0.87, precision of 1.00, but a recall of 0.78, suggesting that the model struggles to predict neutrality accurately. For Class 3 (Disagree), the accuracy was 0.25, with precision of 0.25 and recall of 1.00, indicating that while the model perfectly identifies this class. Overall, the model highlights that the ERP system's impact on business processes is perceived positively, especially among satisfied and very satisfied respondents, with a stronger correlation between ERP implementation and positive business process outcomes.

organization?" demonstrated strong performance, particularly in Class 0 (Strongly disagree), with an accuracy of 0.87, precision of 0.94, recall of 0.94, and F1-score of 0.94, indicating that the model accurately identifies the class of respondents who disagree. Class 1 (Somewhat agree) achieved a perfect accuracy of 1.00, with a precision of 0.73 and recall of 0.84, reflecting a good ability to classify this group with balanced performance. Class 2 (Agree) also performed well with an accuracy of 1.00, precision of 0.78, and recall of 0.88, suggesting that the model effectively identifies individuals who agree with the ERP system's impact. For Class 3 (Strongly agree), the accuracy was lower at 0.25, but the precision was perfect at 1.00, and recall was 0.40, pointing to some challenges in predicting this class but with reasonable accuracy for those classified as strongly agreeing. The overall findings suggest that ERP implementation has a significant positive impact on the efficiency of business processes.

TABLE 5-9: KNN WITH MODEL PREDICTION BASED ON AGREEMENT ON ERP IMPLEMENTATION IMPACT ON BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
Agreement on ERP Implementation Impact on Business Processes [The ERP system has contributed to achieving our business process reengineering goals.]	3	0.90	1.00	0.67	0.80
	4		0.89	0.94	0.92
	5		0.88	0.88	0.88

The KNN model for the target variable "Agreement on ERP Implementation Impact on Business Processes [The ERP system has contributed to achieving our business process reengineering goals.]" demonstrated strong results for higher levels of agreement. Class 3 (Agree) achieved an accuracy of 0.90, with a perfect precision of 1.00, a recall of 0.67, and an F1-score of 0.80, indicating that the model is highly accurate in identifying individuals who agree with the ERP system's impact on business process reengineering (BPR). Class 4 (Strongly agree) showed an accuracy of 0.89, with precision at 0.94 and recall at 0.92, further suggesting a strong correlation between ERP implementation and BPR goals. Finally, Class 5 (Completely agree) maintained solid performance with an accuracy of 0.88, precision and recall both at 0.88, reinforcing the positive impact of ERP systems on business processes. The findings indicate that ERP implementation significantly contributes to achieving business process reengineering goals.

5.1.4 Naïve Bayes for Model Evaluation

TABLE 5-10: NAIVE BAYES WITH MODEL PREDICTION BASED ON OVERALL IMPACT OF ERP IMPLEMENTATION ON BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
How satisfied are you with the overall impact of ERP implementation on business processes in your organization?	0	0.81	1.00	0.45	0.62
	1		0.78	0.96	0.86
	2		1.00	1.00	1.00
	3		0.86	0.57	0.69

The Naive Bayes model for the target variable "How satisfied are you with the overall impact of ERP implementation on business processes in your organization?" showed promising performance across different classes. Class 0 (Dissatisfied) achieved an accuracy of 0.81, with perfect precision (1.00) but a lower recall (0.45), resulting in an F1-score of 0.62, suggesting it identified dissatisfactory instances with high precision but missed some. Class 1 (Moderately Satisfied) performed strongly with an accuracy of 0.78, high precision (0.96), and recall (0.86), reflecting good classification of moderate satisfaction. Class 2 (Highly Satisfied) demonstrated perfect performance, achieving 100% accuracy, precision, and recall, indicating complete success in identifying highly satisfied instances. Class 3 (Very Dissatisfied) had an accuracy of 0.86, with precision (0.57) and recall (0.69), suggesting that the model struggled somewhat to identify very dissatisfied instances, but performed reasonably well overall. In conclusion, the ERP system has had a positive impact on business processes.

TABLE 5-11: NAIVE BAYES WITH MODEL PREDICTION BASED ON ERP SYSTEM STREAMLINES AND IMPROVES THE EFFICIENCY OF BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
To what extent do you agree that the ERP system streamlines and improves the efficiency of business processes in your organization?	0	0.69	0.87	0.69	0.77
	1		0.39	0.82	0.53
	2		0.67	0.59	0.63
	3		0.75	1.00	0.86

The Naive Bayes model for the target variable "To what extent do you agree that the ERP system streamlines and improves the efficiency of business processes in your organization?" demonstrated varied performance across different classes. Class 0

(Disagree) achieved an accuracy of 0.69, with precision of 0.87 and recall of 0.69, showing good classification with a balanced identification of instances. Class 1 (Neutral) had an accuracy of 0.39, with high precision (0.82) but lower recall (0.53), indicating a tendency to classify neutral responses accurately but missed some instances. Class 2 (Agree) showed an accuracy of 0.67, with balanced precision (0.59) and recall (0.63), suggesting a moderate classification performance. Class 3 (Strongly Agree) exhibited the best performance with an accuracy of 0.75, perfect precision (1.00), and high recall (0.86), indicating excellent classification of strongly agreeing instances. Overall, the findings suggest that ERP implementation has a positive impact on streamlining business processes.

TABLE 5-12: NAIVE BAYES WITH MODEL PREDICTION BASED ON AGREEMENT ON ERP IMPLEMENTATION IMPACT ON BUSINESS PROCESSES

Target variable	Class	Accuracy	Precision	Recall	F1-Score
Agreement on ERP Implementation Impact on Business Processes [The ERP system has contributed to achieving our business process reengineering goals.]	3	0.83	0.55	0.67	0.60
	4		0.90	0.81	0.85
	5		0.83	0.92	0.87

The Naive Bayes model for the target variable "Agreement on ERP Implementation Impact on Business Processes" demonstrated promising results across different classes. Class 3 (Strongly Disagree) achieved an accuracy of 0.83, with precision of 0.55, recall of 0.67, and F1-score of 0.60, indicating moderate performance in classifying this group. Class 4 (Disagree) exhibited an accuracy of 0.90, with precision of 0.81, recall of 0.85, and strong F1-score, showing excellent classification. Class 5 (Agree) performed similarly, with an accuracy of 0.83, precision of 0.92, recall of 0.87, and high F1-score, reflecting the model's effectiveness in classifying this group. Overall, the findings suggest that ERP implementation has a positive impact on business process reengineering.

5.1.5 Gradient Boosting Machines for Model Evaluation

TABLE 5-13: GRADIENT BOOSTING MACHINES WITH MODEL PREDICTION

Mean Absolute Error	Mean Squared Error	R-squared
0.0069	8.4497	0.9999

The Gradient Boosting Regressor demonstrated exceptional predictive accuracy in evaluating the impact of ERP implementation on business process reengineering (BPR). The model achieved a Mean Absolute Error (MAE) of 0.0069, indicating minimal deviation between predicted and actual values. The Mean Squared Error (MSE) of 8.4497 further supports the model's precision, highlighting its ability to minimize large errors. Additionally, the R-squared (R^2) value of 0.9999 confirms that the model explains nearly all the variance in the dataset, suggesting a strong correlation between ERP implementation and BPR improvements. These findings indicate that ERP implementation has a significant and measurable impact on enhancing business processes within Sri Lankan organizations.

CHAPTER 6

CONCLUSION

6.1 Study Contribution and Recommendation

This study aimed to evaluate the impact of ERP implementation on Business Process Reengineering (BPR) within Sri Lankan organizations by developing a novel model based on the CRISP-DM framework and assessing it using various machine learning algorithms. The analysis involved several models, including Decision Tree, K-Nearest Neighbors (KNN), Naive Bayes, and Gradient Boosting Machines (GBM), to predict the relationship between ERP adoption and business process improvements. The results demonstrated that machine learning techniques are effective in evaluating ERP implementation outcomes, though their predictive accuracy varied by algorithm. Among the tested models, Naive Bayes and Decision Tree exhibited strong classification accuracy, especially for responses that reflected agreement or strong agreement regarding ERP's impact on BPR. The GBM model delivered particularly impressive performance, with an exceptionally high R-squared value, indicating its powerful predictive capability.

These findings suggest that ERP implementation has a significant influence on process transformation, particularly in streamlining operations, improving efficiency, and achieving reengineering goals. The robust performance of the GBM model confirms the reliability of these predictions, making it a valuable tool for assessing ERP impact on business processes. The study highlights the potential of predictive modelling in ERP impact assessments, providing valuable insights for organizations aiming to optimize their business processes through ERP solutions.

6.2 Limitations of the Research

Despite its valuable contributions, this research is subject to several limitations that should be acknowledged. The dataset used to train and evaluate the machine learning models was derived exclusively from responses collected within Sri Lankan organizations, which may limit the generalizability of the findings to other regions or industry contexts. Additionally, while the study employed a variety of machine learning algorithms, it did not incorporate deep learning models, which could potentially offer enhanced predictive accuracy and improved classification robustness. A further limitation is the class imbalance inherent in the survey dataset, which may have affected the performance of the models. The study did not employ specialized techniques to handle the imbalanced data, such as data resampling methods or class weighting strategies. Furthermore, regression techniques and other statistical approaches were not used for data analysis, which could have provided complementary insights into the relationships among variables and improved model reliability. Another limitation lies in the reliance on survey-based data, which may be subject to subjective biases, as respondents' perceptions can be shaped by organizational culture, personal experience, or situational factors. Moreover, the study did not account for

external influences such as economic conditions, regulatory environments, or the level of organizational readiness, all of which could significantly affect the success and impact of ERP implementation efforts.

6.3 Future Work

Future research can address these limitations and expand upon the current findings in several ways. Incorporating larger and more diverse datasets from various industries and regions would enhance the generalizability of the findings. Additionally, exploring deep learning approaches such as neural networks and reinforcement learning can further refine predictive capabilities and provide more accurate assessments. A critical area for improvement is addressing class imbalance issues in the dataset through methods such as resampling techniques, class weighting, or cost-sensitive learning. This would improve the performance and fairness of the machine learning models, ensuring that underrepresented classes are adequately captured. Furthermore, employing regression techniques and other statistical approaches can provide complementary insights into the relationships between variables, supporting more robust and interpretable models. Another avenue for future work is integrating external factors, such as economic indicators, policy changes, and organizational readiness metrics, to develop a more comprehensive predictive model. Furthermore, incorporating real-time data analytics and dynamic feedback mechanisms into ERP impact assessments can enhance decision-making for organizations. Lastly, conducting longitudinal studies to track ERP implementation over time would provide deeper insights into its long-term impact on business process reengineering, offering organizations more strategic guidance for successful ERP adoption.

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