META-LEARNING-DRIVEN HYPERPARAMETER TUNING FOR ROBUST AND SCALABLE CONCEPT DRIFT TRACKING

Dileesha Navindra Kannangara

248019U

Master of Science: Major Component of Research

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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).

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The above candidate has carried out research for the Master of Science: Major Component of Research Thesis under our supervision. We confirm that the declaration made above by the student is true and correct.

Name of Supervisor: Dr.Uthayasanker Thayasivam

Signature of the Supervisor: Date: 08 Sep 2025

nanaruban Kajadurai

Name of Supervisor: Dr.Sumanaruban Rajadurai I 10 Sep 2025

Signature of the Supervisor: Date:

Name of Supervisor: Dr.Rajitha Navarathna 10 Sep 2025

Signature of the Supervisor: Date:

ACKNOWLEDGEMENT

I would like to extend my heartfelt appreciation to my principle supervisor, Dr. T. Uthayasanker, for his invaluable guidance, steadfast mentorship, and unwavering support throughout the course of this research. His encouragement and insight were instrumental in navigating the challenges of this work, and his commitment to excellence continuously pushed me to elevate the quality of my efforts.

I would also like to express my deepest gratitude to my external supervisors, Dr. Sumanaruban Rajadurai and Dr. Rajitha Navarathna, whose invaluable guidance, insightful advice, and unwavering encouragement have been instrumental throughout the course of my research. Their mentorship not only enriched my academic journey but also inspired me to strive for greater heights. I am truly grateful for their patience, constructive feedback, and constant support, which have been pivotal in overcoming challenges and achieving this milestone.

I am also deeply grateful to the esteemed members of the progress review committee, Dr. Thanuja Ambegoda and Dr. Charith Chitraranjan, for their thoughtful feedback and constructive advice. Their expertise and perspectives played a pivotal role in shaping the direction and refinement of this study.

Finally, I wish to sincerely thank my family and friends for their constant encouragement, understanding, and belief in my abilities. Their unwavering presence has been a source of strength and inspiration, allowing me to persevere and remain committed to my academic goals.

ABSTRACT

Detecting concept drift is a critical task in machine learning, particularly when working with nonstationary real-world data streams that evolve. The ability to identify such drifts promptly and accurately is vital to ensuring that deployed machine learning models remain effective. However, the performance of drift detection algorithms is highly sensitive to the choice of hyperparameters, which must be appropriately configured for each application scenario. Despite this, existing approaches to hyperparameter tuning are often impractical, lack theoretical soundness, or fail to deliver optimal results. To tackle this problem, we introduce ProtoTune—a structured, zero-touch approach for selecting optimal deployment-time hyperparameters in error rate-based drift detection algorithms. Designed to function effectively across a wide range of data stream use cases, ProtoTune eliminates the need for both offline pre-tuning and online retrospective adjustments. This is particularly important because traditional tuning methods are frequently infeasible in real-world settings, where there is often limited prior knowledge, a lack of labeled drift points, and the constraints of streaming data that cannot be revisited once processed. At the core of our approach is an error behavior descriptor, derived from early profiling of a model's error stream. This descriptor informs the identification of a suitable hyperparameter space. We then leverage a meta-learning framework using prototypical networks to learn the relationship between the error behavior descriptor and the ideal hyperparameter configurations. This enables us to provide a scalable and effective solution for deployment-time tuning. To our knowledge, this is the first method specifically developed to address this pressing challenge. Experimental results confirm that ProtoTune consistently surpasses current practical strategies, which often perform no better than random guessing. Our findings underscore the value of leveraging historical error information and offer a systematic solution to a growing operational challenge in adaptive machine learning.

Keywords: Concept Drift Detection, Hyperparameter Optimization, Online Learning, Prototypical Networks

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ABBREVIATIONS

Abbreviation	Description
DDM	Drift Detection Method
EDDM	Early Drift Detection Method
CNN	Convolutional Neural Network
AI	Artificial Intelligence
ADWIN	Adaptive Windowing
KS Test	Kolmogorov-Smirnov test
CUSUM	Cumulative Summation
CPU	Central Processing Unit
HDDM	Hoeffding Drift Detection Method
FHDDM	Fast Hoeffding Drift Detection Method
PSI	Population Stability Index
KL Divergence	Kullback-Leibler divergence
PH	Page-Hinkley
ECDD	Exponential Cumulative Drift Detection
RDDM	Reactive Drift Detection Method
ECCDWT	Exponential Cumulative Drift Detection with a Warning Threshold