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**IDENTIFYING EMOTIONAL VALENCE FROM
FMRI DATA.**

K.E.A.B.I. Edirisinghe

239315X

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Science Engineering and Analytics

Department of Computer Science and Engineering
Faculty of Engineering

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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: ***UOM Verified Signature***

Date: 22/6/2025

The supervisor should certify the Thesis with the following declaration.

The above candidate has carried out research for the Master of Science in Computer Science Specializing in Data Science Engineering and Analytics Thesis under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of Supervisor: Dr. Charith Chithranjan

Signature of the Supervisor:

Date: 22/06/2025

DEDICATION

I dedicate this thesis to all those inspired by the challenge of gaining insight into brain function through data.

For researchers, engineers, and enthusiasts working at the intersection of neuroscience, data analysis, and predictive modeling, your passion for uncovering patterns in neurodata, building intelligent systems, and pushing the boundaries of discovery continues to inspire and drive progress.

ACKNOWLEDGEMENT

I express my deepest gratitude to my thesis advisor, Dr. Charith Chitraranjan, for his invaluable guidance, unwavering support, and expertise throughout this journey. His mentorship and encouragement have been instrumental in shaping the direction and quality of this research.

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ABSTRACT

Identifying emotional valence from fMRI data is a significant step toward understanding how the brain processes affective states. This has important implications in fields such as cognitive neuroscience, mental health, and affective computing. However, decoding emotional valence using machine learning remains a challenging task, especially due to the high dimensionality of fMRI data, inter-subject variability, and the subtle nature of emotional responses. Achieving high classification accuracy is particularly difficult, making it crucial to explore effective feature extraction methods.

This study focuses on comparing the efficiency of two popular feature engineering approaches— General Linear Model (GLM) -based methods and Independent Component Analysis (ICA) —for emotion classification using fMRI data. Specifically, we implement the GLMSingle method for GLM-based feature extraction and compare it against ICA-derived features. The extracted features are evaluated using multiple machine learning classifiers, including Support Vector (SVM), Gaussian Naive Bayes (GNB), Random Forest (RF), and Logistic Regression (LR). We assess classification performance both within subjects and across subjects to evaluate generalizability.

The results show that features derived from the GLMSingle method consistently outperform those from ICA in terms of classification accuracy. This suggests that task-related modeling using GLM provides more discriminative features for emotion prediction than the data-driven ICA approach. The findings highlight the importance of choosing suitable feature engineering strategies in order to improve model performance when decoding affective states from neuroimaging data.

Keywords: fMRI, Emotional Valence, Machine Learning, Feature Engineering, GLM, GLM-Single, ICA

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LIST OF ABBREVIATIONS

Abbreviation	Description
AFNI	Analysis of Functional NeuroImages
AM	Autobiographical Memory
AMUSE	Algorithm for Multiple Unknown Signals Ex- traction
ANN	Artificial Neural Network
ANTs	Advanced Normalization Tools
BCIs	Brain-Computer Interfaces
BIDS	Brain Imaging Data Structure
BOLD	Blood Oxygenation Level Dependent
CICA	Constrained Independent Component Analysis
CSF	Cerebro Spinal Fluid
DCM	Dynamic Causal Modeling
DNN	Deep Neural Network
fMRI	Functional Magnetic Resonance Imaging
FSL	FMRIB Software Library
GICA	Group Independent Component Analysis
GICA-IR	Group Independent Component Analysis with Intrinsic Restraints
GIFT	Group ICA of fMRI Toolbox
GLM	General Linear Model
GNB	Gaussian Naive Bayes
IAPS	International Affective Picture System
ICA	Independent Component Analysis
ICASSO	ICA with Cluster Analysis
ISI	Inter-Session Index Similarity
JADE	Joint Approximate Diagonalization of Eigenma- trices
LOC	Lateral Occipital Cortex
LOO-CV	Leave-one-out Cross Validation
LR	Logistic Regression
MST	Minimum Spanning Tree
MVPA	Multivoxel Pattern Analysis
NIFTI	Neuroimaging Informatics Technology Initiative
RF	Random Forest

Abbreviation	Description
ROI	Region-of-Interest
SIMBEC	Simple Binary Encoding for Classification
SNR	signal-to-noise ratio
SOMs	Self-Organizing Maps
SPM	Statistical Parametric Mapping
STD	Standard Deviation
SVM	Support Vector