

SACAIR2025

Southern African Conference for
Artificial Intelligence Research

AI at the Edge
Pushing Boundaries | Powering Possibilities

Book of
SHORT PAPERS
& ABSTRACTS

Presentations at the Unconference of
the Sixth Southern Africa Conference
for Artificial Intelligence Research

Marriott Hotel Crystal Towers
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Editors:

Clayton K. Baker
Oluwakorede M. Oluyide
Sibonelo Dlamini
Mluleki Bryan Sinqadu
Yuvika Singh



Foreword

It is with great pleasure that we present the Book of Short Papers and Abstracts for the Unconference of the Sixth Southern African Conference for Artificial Intelligence Research (SACAIR2025). Hosted by the University of the Western Cape (UWC), the Unconference took place on 1 December 2025, preceding the tutorials on 2 December and the main conference held from 3–5 December.

The Unconference provides a vital platform for postgraduate students to share their work, gain experience in academic presentation and peer review, and connect with peers, mentors, and industry partners. This year's programme featured a plenary address by Professor Fanelwa Ngece-Ajayi, a keynote by Professor Clement Nyirenda, an industry panel, multiple student paper sessions, and the first dedicated poster session in SACAIR's history.

We received 26 submissions across nine institutions of higher education and industry partners in Southern Africa. Following an evaluation process in which each submission was reviewed by two reviewers and assessed by a team of meta-reviewers, 12 submissions were accepted for Oral Presentation and 11 submissions were accepted for the Poster session. The accepted submissions covered a wide scope within artificial intelligence encompassing both applied and theoretical machine learning in subfields of data-driven deep learning, reinforcement learning and symbolic AI, and extending to Virtual Reality, Cybersecurity and Quantum Computing.

We extend our sincere thanks to all who made this event possible: our mentors for their invaluable feedback, the SACAIR Local Organising Committee for its support, our industry partners for their engagement, and the University of the Western Cape for its warm hospitality. Above all, we thank the authors for submitting their work and congratulate those selected to present. We are encouraged by the creativity and rigour shown by this year's participants and look forward to their continued contributions to advancing responsible and impactful AI research in Southern Africa and beyond.

December 2025

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Message from the General Chairs

The South African Conference for Artificial Intelligence Research was established six years ago with several objectives, with one of the most important being the development of postgraduate students and emerging academics. The Unconference will be the first exposure for many young researchers to an international conference.

The title of this conference was intentionally chosen to reflect the informal and friendly gathering of students, academics and industry, and is intended to provide an environment for students to share their work in progress and receive feedback from experienced researchers and peers. Of special note is the industry panel in which students can interact with former students who went from graduates to highly successful industry professionals in a variety of domains.

Congratulations to the students whose submissions have been selected for inclusion in the Book of Abstracts and to be presented as posters. We are delighted at the significant growth of this event since previous iterations, and hope that the growth continues well into the future.

We extend our appreciation to the participants, including the keynote speakers, industry panel participants, the organising team, faculty, and partners who have worked tirelessly to bring this conference to life. Most importantly, we thank you—the students—for your enthusiasm and dedication. Your contributions are what make this conference vibrant and impactful.

Welcome, and enjoy the conference!

December 2025

Mehrdad Ghaziasgar
Louise Leenen



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Table of Contents

Foreword	ii
Message from the General Committee	iii
SACAIR sponsors	iv
Oral Session	1
Algorithmic and Data-Driven AI (Computer Science)	1
1 Scalable Machine Learning-Based Intrusion Detection for Large-Scale Cloud Environments <i>Luvuyo Ngcobo</i>	
3 Exploring STGNNs for stock market trend prediction using macro-economic data <i>Roelof van Schalkwyk and Deshendran Moodley</i>	
9 Data-Driven Approach for Shelf Life Prediction of Fresh Apple Using IoT and Machine Learning <i>Tharollo Mphahlele and Jean Frederic Isingizwe and Ashwil Klein</i>	
15 An Interpretable Graph-Based Approach to Stress Recognition Using Multi-modal Wearable Signals <i>Ahana Maharaj and Deshendran Moodley</i>	
19 Quality Index Prediction for Fresh Produce Using a Convolutional Neural Network <i>Rovhona Mudau</i>	
23 Advancing Mental Health Diagnostics: Applying Spatial Temporal Graph Neural Networks to EEG Signals for Early Detection of Major Depressive Disorder <i>Dionne Takudzwa Chasi and Deshendran Moodley</i>	
27 Who is the better AI Agent Creator: DQN, PPO, or A2C? Battleground Azul <i>Jené Mercia van Schalkwyk and Mujahid Gasant and Mehrdad Ghaziasgar</i>	
33 Dynamic Spatio-Temporal Graph Neural Networks for Cryptocurrency Trend Classification and Change-point Detection <i>Mazwi Kelvin Nyadzayo and Deshendran Moodley</i>	
35 Deep Reinforcement Learning Applied To Stock Index Trading. <i>Sedzani Meshak Ratshikombo and Mehrdad Ghaziasgar</i>	
41 Comparative Evaluation of Ensemble Machine Learning and Deep Learning Models for Vehicle Theft Location Prediction <i>Khiraam Singh and Edgar Jembere and Matthew Lee Nicholls</i>	
47 Automated Machine Learning for Solving the Combined Algorithm Selection and Hyperparameter Optimisation Problem in Trend Prediction <i>Alex Priscu and Deshendran Moodley</i>	
Socio-Technical and Human-Centred AI	53
53 ChatGPT-Enhanced Suicide Risk Annotation: A Hybrid LLM-Human Framework for Social Media Data <i>Tsholofelo Mokheleli and Tebogo Bokaba and Patrick Ndayizigamiye and Hossana Twinomurinzi and Nom-pumelelo Ndlovu</i>	
Poster Session	59
59 Regulating AI Through Digital Strategy Collective Agreements <i>Vusi Mnguni</i>	

- 63 AI Literacy for Learners in Low-Income Communities: Co-designing with Educators and Learners in Youth Organisation within South Africa
Rachel Oluwatuyi
- 65 Algorithms and Problem Domains for Fully Quantum Machine Learning
Moegamad Jameel and Aleksandar Radovanovic
- 67 The VR-AI-Assisted Power Grid Management Education
Dukyung Choi and Laurent de Laroche Souvestre and Clayton Kevin Baker
- 69 STGNN for Trend Line Prediction on the JSE
Ephraim Awinzoya Adongo and Deshendran Moodley
- 71 Learning Dynamic Dependencies in Spatial-Temporal Systems for Efficient Forecasting
Henok Tenaw Moges
- 73 Local Social Structures as Enablers and Barriers for AI Enabled Medical Drone Delivery: Early Evidence from a Developing Economy
Evode Ndayishimiye and Walter Uys and Edda Weimann
- 75 Network Intrusion Detection Datasets: A Systematic Literature Review
Leonard Mutembei

Index of Authors

77

Scalable Machine Learning-Based Intrusion Detection for Large-Scale Cloud Environments

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The swift transition of the computing landscape and the adoption of cloud computing with a plethora of its benefits have posed a pressing demand for robust, real-time intrusion detection systems (IDS) capable of securing large-scale, dynamic, and resource-shared environments. Traditional security mechanisms and standalone IDS often fail due to scalability, high false positive rates, and performance degradation under high-throughput traffic. This study aims to investigate the design and application of a scalable machine learning-based IDS tailored for large-scale and dynamic cloud infrastructures through the employment of secondary data from the existing literature.

The study evaluates existing ML-based IDS models in terms of detection accuracy, false positive rates, and computational efficiency, specifically highlighting techniques that strike a balance between real-time performance and scalability. By analysing existing literature and empirical results, the paper determines the strengths and limitations of supervised, unsupervised, and hybrid ML-based IDS in cloud environments.

Findings underscore that adaptive feature selection, deep learning approaches, and ensemble methods significantly improved

detection capability while maintaining scalability. The study concludes by highlighting challenges, including dataset representativeness, integration complexities, and resource management that demand attention, enabling resilient, scalable, and efficient ML-based IDS solutions for future cloud environments.

Exploring STGNNs for stock market prediction using macroeconomic data

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Abstract. In this research we aim to explore the performance of Spatial-Temporal Graph Neural Networks (STGNNs) for stock market forecasting when using macroeconomic data. Advanced STGNNs have been developed to improve the ability of machine learning models to make accurate forecasts for time series but most prior work has been conducted on traffic, weather and medical datasets. In addition, where STGNNs have been used for stock price forecasting, datasets have generally contained only stock prices, with macroeconomic indicators excluded despite their potential relevance. To explore the effect of including macroeconomic data in the forecasting task we will compile a new dataset consisting of both stock prices and macroeconomic data. These data will include stock prices for a basket of large companies listed on the Johannesburg Stock Exchange (JSE) as well as an extensive set of macroeconomic indicators. Two state-of-the-art STGNN architectures (MDHAN, MAGNN), a baseline STGNN (GWN) and some earlier DNN architectures (LSTM, CNN) will then be trained to assess their predictive performance on both point and trend forecasting tasks. Performance will be evaluated using standard machine learning error metrics as well as return on investment when using model predictions to make investment decisions. It is expected that our work will demonstrate that augmenting stock price data with macroeconomic indicators improves predictive performance for STGNNs and that the selected advanced STGNNs outperform earlier DNN architectures when forecasting stock prices and trend lines.

Keywords: STGNNs, Stock Market Forecasting, Macroeconomics.

1 Introduction

Many advanced STGNN architectures have been developed for time series forecasting tasks [1,2,3]. However, despite the potential of these architectures to outperform previous financial and economic forecasting techniques, limited efforts have been made to develop and train such models for financial or economic forecasting, as shown by only 16 out of 281 papers found in [1] focusing on financial applications. The research in [1] also indicates that the work conducted in this area has generally relied on stock price data alone despite the clear dependency of stock prices on macroeconomic factors [4]. While several recent studies have evaluated the effect of including macroeconomic

R. van Schalkwyk and D. Moodley

indicators in the feature set, these efforts have explored only simpler machine learning architectures [5,6,7,8]. In addition, even though some work has investigated the use of STGNNs for stock market forecasting on the JSE [9,10], most previous research in this space has focused on either US or Chinese stock markets [1,11,12].

Finally, there is evidence that trend lines [13] can provide better representations of the underlying semantics and dynamics of time series than point data [14,15] while also being of greater interest when making longer term investment decisions [9], which must take macroeconomic factors into account. Given this, accurately forecasting trend lines and change points would be beneficial. However, while [9,16] investigated trend line-based prediction, the surveys presented in [1,2,3] indicate that few other studies have explored trend line forecasting for stock markets using STGNNs.

These results suggest several key limitations in the existing research. First, financial market forecasting using STGNNs is under-studied relative to other areas (e.g. traffic and weather). Second, macroeconomic factors which will likely affect stock market movements are seldom considered in the forecasting task or have only been used to train simpler DNN architectures. Third, trend line-based forecasting could be used to enhance investment decisions, especially when longer term, macroeconomic effects are considered. And fourth, stock market forecasting using STGNNs is under-explored for the JSE compared to US and Chinese markets. The proposed research will seek to address these limitations.

As such, the overall aim of this work is to explore the effect of augmenting stock price data with macroeconomic indicators when training STGNNs for stock market forecasting to evaluate whether such combined data can improve predictive performance.

The key objectives are:

- Compare the predictive performance of STGNN-based models with other DNN architectures for both point and trend forecasting without macroeconomic indicators
- Assess whether the inclusion of macroeconomic indicators improves STGNN and DNN models' predictive performance for point and trend forecasts and whether STGNNs outperform DNNs in this case
- Estimate the Return on Investment (ROI) from using model predictions to make investment decisions by simulating trades based on forecasts
- Visualise and analyse spatial-temporal dependencies to gain insight into how changes in macroeconomic factors affect stocks on the JSE

2 Methodology

The overall approach will be aligned closely with that of [10] and aim to replicate the experimental setups used when GraphWaveNet (GWN) [17], MAGNN [18] and MDHAN [19] were first introduced.

Exploring STGNNs for stock market prediction using macroeconomic data

2.1 Problem formulation

Let the JSE be represented as a dynamic graph $G = (V, E, A)$, where $V = V^{(s)} \cup V^{(m)}$ is the set of nodes, $V^{(s)}$ the set of stocks, and $V^{(m)}$ the set of macroeconomic indicators. The edge set E encodes dependencies between nodes (stocks and macroeconomic indicators), and $A \in \mathbb{R}^{N \times N}$ is the adjacency matrix with $N = |V|$, where $A_{ij} > 0$ indicates a dependency between nodes i and j .

For a sliding window of length L ending at time t , the model input is

$$X^{(t)} = X_{t-L+1:t} \in \mathbb{R}^{N \times L}$$

where each node is observed over T trading days, $X \in \mathbb{R}^{N \times T}$ is the input tensor representing the time series at all nodes V , and $x \in \mathbb{R}^T$ is the time series for an individual node $v \in V$. To formulate the trend forecasting task, we approximate the historical price series $\{y_{v,1}, \dots, y_{v,T}\}$ with a piecewise linear trend sequence (as in [9])

$$\mathcal{T} = \{\langle s_1, l_1 \rangle, \dots, \langle s_K, l_K \rangle\},$$

where each segment $\langle s_k, l_k \rangle$ is characterised by its slope $s_k \in (-90^\circ, 90^\circ)$ and duration $l_k \in \mathbb{N}$ and $v \in V^{(s)}$ is the target stock.

We define the point and trend forecasting tasks as learning functions f^{point} and f^{trend} such that:

$$f^{point}: (G, X^{(t)}) \mapsto \hat{Y}_{t+1:t+H}^{point} \in \mathbb{R}^H, f^{trend}: (G, X^{(t_k)}) \mapsto \langle \hat{s}_{k+1}, \hat{l}_{k+1} \rangle,$$

where $\hat{Y}_{t+1:t+H}^{point}$ are the predicted future prices of the target stock for the next H days and $\langle \hat{s}_{k+1}, \hat{l}_{k+1} \rangle$ are the predicted slope and duration of its next trend segment.

2.2 Dataset

For this research, two datasets will be constructed: one containing only stock prices from the JSE and one augmented with additional, macroeconomic data.

The stock price dataset will include the JSE ALSI and a basket of individual stock prices for large companies listed on the JSE. The augmented dataset will include a set of relevant macroeconomic indicators as well as these stock prices. As a minimum the macroeconomic data will cover GDP, inflation, central bank interest rates, and exchange rates for both South Africa and the USA, as well as gold and oil prices. If possible, further macroeconomic data will be added, including:

- Key equity market indices like the S&P 500, MSCI World, and MSCI China
- Bond yields (e.g. 10-year, 2-year) for both South Africa and the USA
- Unemployment rates, trade balances, and market volatility

2.3 Data Preprocessing

Data preprocessing will proceed in accordance with the approaches of [9,10] to interpolate and/ or impute missing data points, normalise input data (via Z-score

R. van Schalkwyk and D. Moodley

normalisation), segment the data into training, validation and test sets, and generate the input trend line segments for the trend forecasting task. Given that stock market data will likely be available daily while some macroeconomic indicators will only be available monthly or quarterly, an approach using temporal aggregation, interpolation or mixed-frequency learning will be developed to allow effective combination of the stock and macroeconomic time series. Generating the trend line segments will likely follow the bottom-up, sliding window method used by [15] and adapted in [9], though other techniques will be considered.

Finally, the benefit of augmenting the dataset with technical features such as moving averages, momentum and volatility measures will be investigated as previous work suggests the addition of such features can improve model performance [20].

3 Experimental Setup

A standard STGNN training pipeline, closely following the approaches in [10,17,18,19], with data preprocessing as described above, will be implemented. Model training, including hyperparameter optimisation to maximise performance, will be undertaken using walk-forward validation with final evaluation performed on the holdout set as per [9]. Common machine learning metrics (MAE, RMSE, MAPE as used in [10,17]) will be calculated to compare model performance. Also, a Return on Investment (ROI) metric will be derived based on simulated trading using the models' predictions, similar to the Investment Return Ratio (IRR) used in [19].

To determine the effect of including macroeconomic indicators in the dataset and which architectures provide the most accurate forecasts, a comparison will be made between models' performance on the two datasets used, as well as against each other, for both the point and trend forecasting tasks. Finally, using visualisations of the adjacency matrices for the trained STGNNs, the effects of macroeconomic changes on JSE stocks will be investigated.

4 Anticipated Outcomes

It is anticipated that this research will make an important contribution in determining whether the inclusion of macroeconomic features in input data improves STGNNs' predictive performance while providing insight into how macroeconomic changes affect stock prices on the JSE. Specifically, this research will provide a performance comparison for point and trend stock forecasting between STGNNs and other, simpler DNN architectures trained on datasets with and without macroeconomic data. Given STGNNs' ability to learn complex interdependencies between nodes in a network, it is hypothesised that predictive performance will improve as a result of the inclusion of macroeconomic data.

In addition, it is expected that STGNN-based architectures will outperform the other DNN architectures on this task and that the research will establish that one or two STGNN architectures are most suitable for stock price and trend forecasting using macroeconomic indicators.

Exploring STGNNs for stock market prediction using macroeconomic data

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R. van Schalkwyk and D. Moodley

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Data-Driven Approach for Shelf Life Prediction of Fresh Apple Using IoT and Machine Learning

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Abstract. Significant economic losses occur as a result of changes that occur during post-harvest operations of agro-products (e.g., apples). Recent efforts to curb losses globally have promoted data-informed approaches to postharvest processes management. The current study considered and proposed machine learning approaches like multiple linear regression (MLR), random forest (RF), support vector machine (SVM), and feedforward neural network (FNN) models to predict the shelf life of fresh apples. IoT sensors paired with LoRaWAN were used to monitor environmental parameters such as temperature, humidity, VOC levels, and CO₂ estimates. Formal laboratory techniques were used to measure apple quality attributes such as background peel colour, texture, mass, size, total soluble solids, titratable acidity, etc. Results indicated that the FNN model outperforms the others with an R² value of 0.97859, indicating an excellent fit. The RF model also shows strong performance with an R² value of 0.97407. RF model has the lowest MAE (0.05587), indicating the best predictive accuracy among the models. From the scatter plots, B (RF) and D (FNN) indicate the strongest correlation between actual and predicted shelf life, indicating high accuracy. Overall, the FNN and RF models demonstrate superior performance.

Keywords: Agro-products · Modelling · Shelf Life · Machine Learning · Prediction

1 Introduction

Food shelf life prediction technology monitors and regulates both environmental and quality attributes [3]. There are two primary approaches to figuring out how long food will last on the shelf: the first is to use dynamic equations or mathematical models that use biochemical indicators to characterize changes in food quality over time and then calculate the food's shelf life [8]. Under certain products and complex environmental conditions, the findings may not be adequate, even though this method can clarify the quality changes during food storage. Machine learning methodology is a data-driven method that uses training data

Mphahlele et al.

to learn and forecast future results. This method creates predictions by examining patterns and relationships in vast volumes of data, as opposed to predefining explicit rules or algorithmic processes [10, 9, 2, 7].

Therefore, the current study was conducted to propose robust predictive models capable of accurately estimating the shelf life of apples. This study intends to address the challenges of shelf life prediction by utilizing machine learning. These challenges include the dynamic nature of environmental conditions, the interaction of various quality parameters, and the reactions of different food types to storage conditions.

2 Materials and Methods

Freshly harvested apples were stored at -0.5°C for a period of two months in a cold room. The physical and chemical properties of the apples were captured under control, and temperature break. Some of the apples were moved to a different cold room and observed at a high temperature of at least 3°C . Physio-chemical parameters such as peel colour, firmness, moisture content, mass, size, titratable acidity, total soluble solids, pH, and variables related to multiple attributes of fresh apples, such as temperature, humidity, gas concentrations, breathe volatile organic compounds (VOC), carbon dioxide estimate equivalent (CO_2e), final temperature and percentage decay were taken. The LoRaWAN sensors were used to capture and collect data. The dataset used for model training contained a total of 713 data points with 16 features and Shelf life in days as the response variable. To ensure model robustness, the combined dataset was split into training (80%) and testing (20%) sets. This diverse was then pre-processed to handle missing values, outliers, and scale numerical features appropriately. The proposed and developed models were MLR, RF, SVM, and FNN. To validate the prediction model's performance, a testing dataset was used to evaluate its R^2 value, MAE, MSE, and RMSE. Scatter plots were used to visualise the relationship between actual and predicted shelf life.

3 Results and Discussion

Table 1. An overview of results based on performance metrics

Metric	MLR	RF	SVM	FNN
R^2	0.69480	0.97407	0.95332	0.97859
MAE	1.26061	0.05587	0.16751	0.30550
MSE	2.63010	0.22346	0.40223	0.18449
RMSE	1.62176	0.47272	0.63422	0.97856

The FNN model outperforms other models with an R^2 value of 0.97859, indicating an excellent fit. The RF model also shows strong performance with

Data-Driven Approach for Shelf Life Prediction of Fresh Apple

an R^2 value of 0.97407. The SVM model follows closely with an R^2 value of 0.95332, while the MLR model lags behind with the least R^2 value of 0.69480. In terms of error metrics, the RF model has the lowest MAE (0.05587), indicating the best predictive accuracy among the models. The FNN model has a slightly higher MAE (0.30550) but the lowest MSE (0.18449) among all models, except RF's MSE is slightly higher than FNN's. The RF's MSE of 0.22346 is higher than FNN's MSE of 0.18449. The RF model has a slightly higher MSE (0.22346) than FNN. The MLR model consistently shows the highest errors across all metrics (Table 1). According to [6], MLR generally performs worse in complex datasets compared to more sophisticated models like RF, SVM and FNN. Therefore, even though MLR is efficient and interpretable, machine learning models might perform more accurately than MLR does. Despite these drawbacks, MLR is nevertheless a valuable baseline model since it is straightforward and easy to understand, which makes it appropriate for preliminary research [6].

The four scatter plots (A-D) provide a visual comparison of the models proposed for shelf life prediction of apples. Plots B (RF) and D (FNN) show the strongest correlation between actual and predicted shelf life, indicating high accuracy (Fig. 1). The FNN model exhibits lower residual error, lower variance, and a significant alignment between actual and predicted values. Outperforming MLR and even competing well with RF or SVM, which frequently exhibit greater dispersion due to sensitivity to noise or limited flexibility in capturing subtle variations [5, 11]. The dependability of predictions may be impacted by data variability, measurement error, or inadequate feature information, as shown by a few dispersed outliers. Although not significant, these little variations point to areas that could need improvement [4, 1]. Overall, the FNN and RF models demonstrate superior performance, with FNN having a slight edge in terms of R^2 and MSE, while RF has the best MAE.

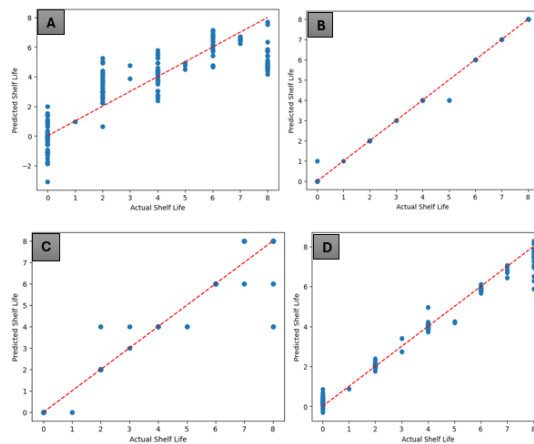


Fig. 1. Scatter plots of actual versus predicted shelf life for MLR (A), RF (B), SVM (C), and FNN (D).

Mphahlele et al.

4 Conclusion

The results suggest that RF and FNN were the most effective in predicting the shelf life of fresh apples based on a demonstrated strong predictive capability, outperforming the MLR model and comparing favourably to other models in the literature. The robust performance of these models indicates a high degree of accuracy and reliability, making them promising models for use in real world shelf life prediction scenarios. Ultimately, the FNN and RF models show great potential for improving the accuracy and efficiency of apple shelf life prediction. Further testing and validation of the models on longer-term storage data and other types of fruit are highly recommended.

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An Interpretable Graph-Based Approach to Stress Recognition Using Multi-modal Wearable Signals

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Abstract. Stress detection is a critical component of modern health-monitoring systems. While most existing approaches rely on electroencephalography (EEG) signals due to their direct association with brain activity, such methods require expensive and impractical laboratory equipment. This study investigates the use of Spatio-Temporal Graph Neural Networks (ST-GNNs) for stress recognition using the WESAD dataset, a multimodal collection of peripheral signals captured by wearable sensors. Specifically, two established ST-GNN architectures, GraphWaveNet and Attention-Based Spatio-Temporal Graph Convolutional Networks (ASTGCN), will be implemented and empirically compared against state-of-the-art methods, Husformer and ConvNeXt with cSAGAN. To the best of our knowledge, this is the first application of ST-GNNs to stress recognition based on wearable sensor data. ST-GNNs are particularly well-suited for this task due to their ability to model both inter-signal (spatial) and temporal dependencies via adaptive adjacency matrices. This work aims to address the challenges of accurate classification and interpretability in wearable stress recognition using ST-GNNs.

Keywords: Stress detection · Multimodal Data · ST-GNN · Interpretability

1 Introduction

Stress recognition is a central topic in affective computing and has significant implications for future healthcare systems. Automated stress monitoring can, for instance, assist individuals with Parkinson’s disease who are unable to express stress or anxiety verbally (1). Previous studies primarily relied on EEG-based classification since emotional states directly correlate with brain activity. ST-GNNs have also been successfully applied to EEG data due to their ability to model spatial relationships between brain regions (6).

However, EEG acquisition requires costly equipment and strict laboratory conditions, making it impractical for real-world applications. In contrast, wearable sensors can capture peripheral physiological signals such as ECG, EMG, and respiration (RESP), which exhibit subtle variations indicative of stress. This research therefore explores applying ST-GNNs, traditionally used for EEG analysis, to the WESAD (Wearable Stress and Affect Detection) dataset (5).

Recent work in wearable stress detection has focused on convolutional and transformer-based methods due to their strong classification performance. Nonetheless, graph-based deep learning approaches remain underexplored, despite their inherent ability to capture inter-modal and temporal dependencies through adaptive adjacency matrices. Moreover, interpretability, which is critical in healthcare applications; remains limited in most deep learning approaches, which often function as opaque “black-box” models.

Therefore, the research aim of this work is to investigate the suitability of Spatial Temporal Graph Neural Networks (ST-GNNs) for multimodal stress recognition classification using wearable

signals. To our knowledge, the application of ST-GNNs for stress detection using wearable signals is novel.

The research objectives to achieve this aim are as follows:

- Empirically evaluate the classification performance of two ST-GNN architectures (GWN, AST-GCN) over state of the art approaches in multi-modal, wearable emotion detection.
- Leverage the interpretability of adaptive adjacency matrices in ST-GNNs to investigate strength and inter-relationships of different wearable signals in stress detection.

2 Methodology

2.1 Problem Formulation

Let the multimodal dataset be represented as a graph $G = (V, E)$, where each node $v_i \in V$ corresponds to a distinct peripheral modality (e.g., ECG, EDA, EMG) and each edge $(v_i, v_j) \in E$ encodes the dependencies between each modality. Every subject is associated with vector z of static demographic features (i.e. age, height, weight, sex, dominant hand). The adjacency matrix $A \in \mathbb{R}^{N \times N}$ represents the self learned graph connectivity between nodes, where $N = |V|$ is the total number of nodes.

The input to the model consists of multiple signal segments obtained via a sliding window of length S , denoted collectively as $X \in \mathbb{R}^{N \times S}$ for a single segment. Each row of a segment corresponds to a node (channel) and each column corresponds to a timestep within the window.

The model learns a mapping function

$$f : [X, A, z] \mapsto y$$

Let $\mathcal{Y} = \{\text{baseline, amusement, stress}\}$ denote the set of discrete emotional labels, where $y \in \mathcal{Y}$.

This formulation allows a spatial-temporal graph neural network to jointly exploit (i) dependencies between modalities encoded in the graph structure A , (ii) temporal dynamics within each segment across all nodes, and (iii) subject-specific characteristics captured by z

2.2 Baseline Models

This study employ the baseline models: Husformer (a transformer-based model) (7), and ConvNeXt with cSAGAN (a convolutional encoder coupled with a generative adversarial network for data augmentation) (4). Both algorithms represent current state-of-the-art architectures for emotion recognition from wearable data.

2.3 Spatial Temporal Graph Neural Networks

In the proposed framework, each wearable sensor is represented as a node within a graph, with dynamic edges capturing spatial and temporal relationships via an adaptive adjacency matrix. The GraphWaveNet model (8) employs learnable embeddings within its diffusion process to dynamically construct this adjacency matrix, effectively modeling spatial and temporal dependencies. The Attention-Based Spatio-Temporal Graph Convolutional Network (ASTGCN) (2) extends this design with attention mechanisms across spatial-temporal modules operating at varying temporal rates. The inclusion of attention enhances both interpretability and classification accuracy, aligning with the current research trend towards attention-based multimodal learning.

3 Methodology

The experimental workflow begins with preprocessing the multimodal physiological data from the WESAD dataset, which includes signals such as ECG, EMG, and respiration. The data are segmented into overlapping windows using a sliding-window approach to capture short-term temporal dependencies. Each channel is then standardized via z-score normalization to ensure uniform scaling across modalities. The proposed models (GraphWaveNet, ASTGCN, and the baseline architectures) are trained and evaluated using a Leave-One-Subject-Out (LOSO) cross-validation scheme, in which each participant’s data serves as the test set once, and the overall performance is computed as the mean across all iterations. Model evaluation employs accuracy, F1-score, and recall as primary metrics, where recall is emphasized due to its importance in minimizing false negatives, which are particularly costly in healthcare contexts. Furthermore, recall and F1-score are robust to class imbalance, a known characteristic of the WESAD dataset (5). This methodology ensures a rigorous and fair comparison of model performance while addressing the practical challenges inherent in wearable stress recognition. Furthermore, the interpretability of the model can be explored using the adjacency matrix. Most deep learning models applied to multimodal wearable data often lack transparency, making their decisions difficult to interpret. Existing explainability frameworks in this domain, such as Guided Backpropagation and GradCAM (3), are typically post hoc, computationally expensive, and unable to capture inter-signal dependencies. In contrast, the adaptive adjacency matrix in ST-GNNs is inherently learned during training, providing interpretability at no additional computational cost. This matrix quantifies both the relative importance of signals and their cross-modal interactions, offering intrinsic explainability suited for healthcare applications.

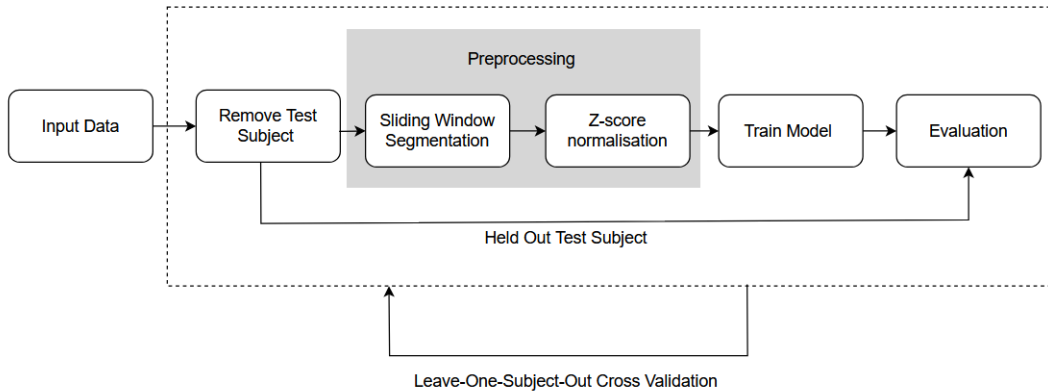


Fig. 1. Machine Learning Pipeline illustrating the Leave-One-Subject-Out cross validation scheme

4 Conclusion

Given the proposed design and experimental framework, we expect the ST-GNN architectures (GraphWaveNet and ASTGCN) to achieve comparable or superior classification performance relative to current state-of-the-art methods, while offering improved interpretability for stress recognition using wearable data.

Future research should validate the proposed models on additional emotional-state datasets to ensure generalizability. While LOSO cross-validation is common in biomedical studies, it introduces potential bias since all data are eventually used for both training and testing. Ideally, a separate held-out test set should be employed, though the limited dataset size currently constrains this approach. Expanding the dataset would enhance robustness and generalization.

Additionally, exploring data augmentation techniques could improve model performance. Augmentations such as gaussian noise, or synthetic data generation via generative adversarial networks, have been shown to enhance deep learning outcomes in data-scarce domains. Applying such strategies may further improve the classification accuracy of ST-GNN models in stress detection.

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Quality Index Prediction for Fresh Produce Using a Convolutional Neural Network

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Abstract. In agricultural supply chains, determining the quality of fresh produce is a crucial task. Inaccurate or delayed inspections can result in large post-harvest losses. In this work, a convolutional neural network (CNN)-based system for image analysis-based fresh produce quality index prediction is presented. With a test accuracy of 90.81%, the model—which is based on the MobileNetV2 architecture—was trained on a dataset of more than 30,000 annotated images. The system’s deployment using TensorFlow.js, which permits real-time, client-side inference in a web browser without cloud connectivity, is a significant contribution. For farmers and distributors, this offers an affordable and easily accessible tool. The system provides storage suggestions, a confidence score, and a freshness classification.

Keywords: Convolutional Neural Network · Computer Vision · Fresh Produce · TensorFlow.js · Edge AI

1 Introduction

An estimated 30% of fresh produce is wasted each year as a result of improper handling and insufficient quality assessment, making post-harvest food loss a significant worldwide concern [1]. The current standard, manual inspection, is ineffective and subjective. As a result, there is a need for accessible, automated systems for accurate, real-time quality evaluation. This study presents a convolutional neural network-based machine learning system that forecasts the fresh produce quality index. Because it uses TensorFlow.js to deploy the efficient MobileNetV2 architecture client-side, the system can make predictions instantly without relying on cloud infrastructure, which makes it appropriate for low resource environments.

2 Related Work

With CNNs exhibiting high accuracy in tasks like plant disease detection, the use of deep learning in agriculture has advanced considerably [2]. The assessment of quality, however, poses a unique problem since it calls for the prediction of continuous freshness metrics as opposed to the categorization of discrete disease states.

Rovhona Mudau

Effective deep learning models that are appropriate for edge devices have been made possible by recent architectural advancements like MobileNet [4]. Additionally, a promising paradigm for client-side inference is provided by browser-based deployment using TensorFlow.js [5], which gets rid of cloud dependencies and privacy issues. Although these technologies have been investigated for disease detection in existing systems, there is still limited use of them for predicting the quality of fresh produce. Accessibility is limited by the fact that many quality assessment systems still rely on specialized hardware or cloud processing. By offering a browser-based, CNN-driven system for real-time quality prediction that runs solely on the client side, this work fills this gap.

3 Methodology

3.1 Dataset and Preprocessing

The model was trained on the Fresh and Rotten Classification Dataset [?], containing 30,357 images across multiple produce types. The dataset was partitioned into training (70%), validation (15%), and test (15%) sets.

Preprocessing: All images were resized to 224×224 pixels and normalized. Data augmentation was applied to improve generalization, including random rotations ($\pm 20^\circ$), horizontal/vertical flipping, and brightness/contrast adjustments.

3.2 Model Architecture and Training

The system uses MobileNetV2, a foundational feature extractor that has been pre-trained on ImageNet, in a transfer learning approach. The original classification head was swapped out for a custom top layer in order to modify the model for the binary classification task (fresh vs. rotten). A Global Average Pooling layer, a Dense layer with 128 units and ReLU activation, a Dropout layer with a rate of 0.5 to prevent overfitting, and a final Dense layer with a sigmoid activation function for output make up this custom head. TensorFlow was used to train the model. The Adam optimizer was used in the training configuration, with binary cross-entropy serving as the loss function and a learning rate of 0.0001. Using an early stopping callback that tracked validation loss with a patience of 5 to avoid overfitting, training was carried out for a maximum of 25 epochs with a batch size of 32. In order to facilitate client-side deployment in the web browser, the model was transformed into the TensorFlow.js format after training was finished.

3.3 System Deployment and Evaluation

A web application was created using the trained model. There is no need for server infrastructure because all inference is done client-side in the user's browser. Using 100 test images and the browser's Performance API, inference time was calculated. Standard metrics such as accuracy, precision, recall, and F1-score were used to assess performance.

4 Results and Discussion

4.1 Model Performance

The model achieved a test accuracy of 90.81%. Performance across classes was balanced, as detailed in Table 1. The high precision and recall indicate robust classification without significant bias.

Table 1: Classification Performance on Test Set

Class	Precision	Recall	F1-Score	Support
Fresh	0.91	0.92	0.91	3,400
Rotten	0.90	0.89	0.90	3,338
Weighted Avg.	0.91	0.91	0.91	6,738

4.2 Deployment and Inference

Real-time predictions are successfully displayed in the browser by the system. On typical hardware (Intel i5, 8GB RAM), the average inference time was less than 10 seconds, indicating viability for real-world application. Network latency and data privacy concerns related to cloud-based solutions are eliminated by this client-side execution.

5 Conclusion and Future Work

This study introduced a CNN-based fresh produce quality prediction system that works well in a web browser. High accuracy was attained by the model, and its client-side deployment makes it a useful and approachable tool. In order to develop a multimodal prediction system, future research will concentrate on combining visual analysis with data from IoT sensors (such as temperature and humidity). This would further lower post-harvest losses and allow for more accurate, context-aware shelf-life forecasting.

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Advancing Mental Health Diagnostics: Applying Spatial Temporal Graph Neural Networks to EEG Signals for Early Detection of Major Depressive Disorder

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Abstract. Major Depressive Disorder (MDD) is among the most prevalent psychiatric conditions, affecting nearly one in six adults worldwide. Current diagnostic methods rely on subjective self-report questionnaires, underscoring the need for objective, neurophysiological biomarkers. Electroencephalography (EEG) provides a non-invasive, high temporal resolution measure of brain activity that can support such discovery, yet traditional EEG analysis often depends on handcrafted features and static spatial models that fail to capture dynamic neural interactions. This study repurposes Spatio-Temporal Graph Neural Networks (STGNN's) originally developed for traffic forecasting—for EEG-based MDD detection. By representing electrodes as graph nodes connected through time-evolving edges, the model learns dynamic functional connectivity patterns that differentiate depressive from healthy brain states.

Keywords: EEG · Major Depressive Disorder · Spatio-Temporal Graph Neural Networks · Dynamic Graph Learning · Mental Health Diagnostics.

1 Introduction

Major Depressive Disorder (MDD) is characterized by persistent disturbances in mood, cognition, and physiology. It affects approximately one in six adults globally, including an estimated 29.19 million individuals in Africa [2]. The diagnosis currently relies on self-report questionnaires, which are prone to subjectivity and diagnostic variability, highlighting the need for reliable objective biomarkers.

Electroencephalography (EEG) offers a promising avenue for neurophysiological assessment, as a non-invasive technique that can capture rapid brain dynamics associated with depressive states. Recent studies combining EEG with machine learning and deep learning have shown encouraging results in identifying depression related neural signatures [3][4]. However, conventional pipelines

Dionne Takudzwa Chasi^{1,2} and Deshendran Moodley^{1,2}

rely on static connectivity assumptions or handcrafted spectral features that fail to represent the complex, time varying nature of brain networks.

Spatio-Temporal Graph Neural Networks (STGNN) provide a powerful alternative for modeling such non-stationary patterns. By treating multichannel EEG as a dynamic graph where electrodes are nodes and their relationships evolve over time STGNNs can jointly learn spatial and temporal dependencies. Attention mechanisms further enable the model to focus on the most informative brain regions and critical time intervals. This study investigates the use of STGNNs for detecting MDD from EEG data, aiming to advance objective and interpretable computational tools for mental health diagnostics.

2 Problem Formulation

We define an EEG time series EEG recording as

$$X = \{x_1, x_2, \dots, x_T\}, \quad x_t \in R^C,$$

where T is the number of time steps and C is the number of EEG channels (electrodes). Each x_t represents a observation vector across all electrodes at time t .

To model both spatial and temporal dependencies, we construct a dynamic graph representation:

$$G = (V, E), \quad |V| = C,$$

where each node $v \in V$ corresponds to an EEG channel, and edges $e \in E$ encode functional connectivity (e.g., correlation or learned adjacency) between channels.

Given a dataset

$$D = \{(X_i, y_i)\}_{i=1}^N,$$

where $X_i \in R^{C \times T}$ is the EEG signal of subject i and $y_i \in \{0, 1\}$ is the label indicating the absence (0) or presence (1) of Major Depressive Disorder (MDD), the aim is to learn a mapping

$$f_\theta : R^{C \times T} \rightarrow \{0, 1\},$$

parameterized by θ , such that

$$\tilde{y}_i = f_\theta(X_i, G),$$

where $\tilde{y}_i \in \{0, 1\}$ denotes the predicted class label for subject i .

3 Methodology

The methodology of this study involves a systematic pipeline for the EEG based detection of MDD, standardized preprocessing, deep learning model training, and model evaluation. EEG recordings are sourced from two datasets: the Hospital Universiti Sains Malaysia cohort (HUSM) and the publicly available Multimodal Open Dataset for Mental-disorder Analysis (MODMA) dataset [7, 6]. Raw

STGNNs for Early MDD Detection from EEG

signals undergo comprehensive preprocessing, including band pass filtering, application of a 50 Hz notch filter, independent component analysis (ICA) for artifact removal, and segmentation into short, overlapping epochs. This segmentation strategy is employed to preserve critical temporal dynamics within the EEG signals [3]. The processed EEG samples are subsequently utilized for training and evaluating deep learning models under a k -fold cross-validation scheme. This approach is implemented to enhance the robustness of findings and prevent data leakage and ensuring the generalizability of the results.

The STGNN's are benchmarked against an established EEG baseline for MDD (EEGNet [1]) and a canonical STGNN baseline (Graph WaveNet [8]). Performance is reported using accuracy, precision, recall, F1-score, specificity, and the area under the receiver operating characteristic curve (AUROC).

4 Preliminary Results

Convolutional Neural Network (EEGNet)

Our initial baseline evaluation utilized EEGNet [1], a widely recognized compact Convolutional Neural Network for EEG-based brain-computer interfaces. Following the application of our complete preprocessing pipeline (band-pass filtering, 50 Hz notch filtering, independent component analysis for artifact removal, and epoch segmentation), EEGNet achieved the following performance metrics on the HUSM dataset [7].

Table 1. Model Performance Metrics

Metric	Value
Accuracy	0.9274
Precision	0.8462
Recall	0.9666
F1 Score	0.9167

These results collectively validate both the robustness of our pre-processing workflow and the suitability of EEGNet as a strong reference point. Subsequent experiments will build upon this established baseline to assess whether more advanced STGNN's can capture time varying neural connectivity more effectively and further improve diagnostic performance.

5 Discussion and Expected Outcomes

The initial results using EEGNet provided a strong baseline validation for the preprocessing pipeline, achieving 92.74% accuracy and recall 0.9666 on the HUSM

Dionne Takudzwa Chasi^{1,2} and Deshendran Moodley^{1,2}

dataset. These findings confirm the feasibility of objective detection using established deep learning methods.

The expected results involve benchmarking advanced STGNNs against this baseline. The study anticipates that architectures such as DSTGNN, AGCRN, and ASTGCN which excel at modeling dynamic spatial-temporal correlations in domains like traffic forecasting will capture the evolving functional connectivity in EEG signals more effectively than static models.

The ultimate goal is to determine whether these dynamic graph learning approaches can yield superior diagnostic utility and enhance performance beyond the initial EEGNet results. This analysis will establish whether the transfer of STGNN techniques is beneficial in advancing objective MDD detection.

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Who Is The Better AI Agent Creator: DQN, PPO, Or A2C? Battleground Azul

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Abstract. This short paper presents (i) the development of a custom Python simulation environment for the two-to-four-player board game *Azul* (focusing more on two players), and (ii) presents a discussion on the future implementation of a value-based algorithm (DQN), a policy-based algorithm (PPO), and a value-policy-based algorithm (A2C) to create intelligent agents within the simulation. Designed to be AI Gym-compliant, the *Azul* simulator closely mirrors the original board game’s rules and gameplay, enabling realistic training of deep reinforcement learning agents. The environment supports accurate AI-vs-AI self-play experiments and offers a versatile platform for ongoing research in strategic decision-making. The performance of the three algorithms is compared to determine which achieves the best results.

Keywords: Azul board game · Python simulation · AI Gym · deep reinforcement learning · DQN · PPO · A2C.

1 Introduction

Reinforcement learning (RL) enables agents to learn optimal behaviours through interaction with environments. When combined with deep neural networks, deep reinforcement learning (DRL) can model complex, high-dimensional state and action spaces [17]. The agent-environment cycle (Figure 1, Section 3) illustrates how agents observe, act, and adapt to maximize rewards.

RL has been applied across robotics [5], autonomous driving [10], and gaming [9], where the design of the action space strongly affects learning performance. Action spaces are typically discrete, continuous, or hybrid: discrete for Atari games [1], continuous for control tasks [17], and hybrid when discrete actions include continuous parameters [6].

This paper presents a Python-based *Azul* simulation for training and evaluating DRL agents (DQN, PPO, and A2C) in a custom Gymnasium environment.

J. M. van Schalkwyk *et al.*

Structure of the Paper

Section 2 reviews DRL action spaces and related work. Section 3 outlines the RL framework, Section 4 describes DQN, PPO, and A2C, and Section 5 details the *Azul* environment, followed by conclusions and future work in Section 6.

2 Literature Review

Deep reinforcement learning (DRL) combines RL with deep neural networks, allowing agents to learn complex decision-making in high-dimensional environments [11]. DRL methods are usually value-based, policy-based, or actor-critic, depending on whether they optimize value estimates, policies, or both.

2.1 Action Spaces and Algorithms

Action spaces define how agents interact with environments and can be discrete, continuous, or hybrid. DQN [8] learns value functions for discrete actions, PPO [12] updates policies with stability, and A2C [7] combines policy and value learning. These methods perform well in environments like Atari and Go [13].

DRL has also been applied to multi-agent board games. Xenou *et al.* [16] used DRL with action-dependent state features and parallel LSTMs in *Settlers of Catan*, outperforming heuristics and showing DRL can handle sequential, stochastic, and competitive games.

2.2 Connection to *Azul*

Azul is a 2–4 player board game inspired by Portuguese tiles (*azulejos*) [14], where players act as tile layers, selecting factories, tiles, and placement lines, a hybrid action space suitable for DQN, PPO, and A2C. It is ideal for DRL research because it provides a controlled yet non-trivial decision environment, which balances short and long term strategy, involves limited resources and partial information, incorporates rewards and penalties, and supports Python-based testing of multi-agent DRL agents.

3 Reinforcement Learning Framework

RL methods are broadly categorized as model-free, which learn directly from interaction, and model-based, which build predictive models of the environment to guide decisions [3], [4]. Two key concepts are the Markov Decision Process (MDP) and the exploration-exploitation dilemma: the former defines the decision structure, while the latter balances discovering new actions with maximizing known rewards.

At each time step t , an agent observes a state S_t , selects an action A_t , and receives a reward R_t and next state S_{t+1} [15] (Figure 1).

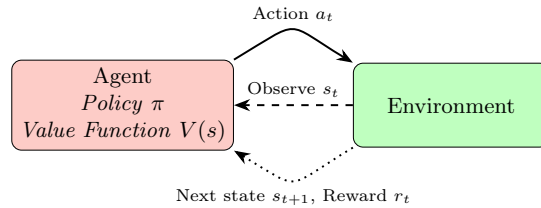


Fig. 1: Agent-environment interaction in reinforcement learning. Adapted from [15], Sec. 3.1.

4 Reinforcement Learning Algorithms for *Azul*

Model-free methods learn from experience without modeling environment dynamics. This study uses three algorithms: DQN, PPO, and A2C. DQN [8] is value-based, suited for discrete actions, and learns via Q-values [2]. PPO is policy-based, for continuous or hybrid actions, and learns action probabilities with stable updates [12]. A2C [7] combines value and policy updates, handling both discrete and continuous spaces [2].

All three follow the standard RL cycle (Figure 1), observing states, selecting actions, and receiving rewards. In *Azul*, the agent chooses a factory, tile colour, and placement row, forming a hierarchical discrete decision process suitable for all three algorithms.

5 Simulation and Implementation

5.1 Azul Game Overview and Motivation

The board game *Azul*, was released in 2017, and in 2018, won the prestigious Spiel des Jahres (Game of the Year) award. Designed by Michael Kiesling and published by Plan B Games, it is a board game in which players draft tiles to fill their boards according to pattern rules, aiming for the highest score. Its sequential decisions, hierarchical action space, and clear reward structure make it well-suited for DRL research, enabling agents to explore strategy, scoring optimization, and competitive gameplay.

5.2 Action Space and Environment Design

The simulation models *Azul*'s core elements: state space, action space, and reward function. The state space includes factory disks (5, 7, or 9 for 2, 3, or 4 players, respectively), the center area, player boards (pattern lines, walls, floor lines), and turn order. Actions involve selecting a tile colour and source (factory or center) and placing it in one of five pattern lines, with invalid actions filtered. And rewards are given for placements, penalized for leftovers, and include bonuses for completed rows (+2), columns (+7), and complete sets of 5

J. M. van Schalkwyk *et al.*

colours (+10). The environment follows the Gymnasium API with *reset()* and *step()*.

5.3 Technical Implementation

Developed with Honours student Mujahid Gasant, the implementation uses Python with Gymnasium for environment handling, NumPy for numerical operations, and PyGame for visualization. The architecture has three main classes: BoardGame2D for rendering, BoardGameState for Azul’s logic including tile drafting, scoring, and flow, and AzulEnv, which wraps the game as a Gym-compatible environment managing resets, state transitions, rewards, and termination. This modular implementation provided the foundation for the environment logic, visualization, and Gymnasium integration used in this study.

Figure 2 illustrates a turn for Players 1 and 2: Player 1 has the first-player marker but a -1 floor penalty, scoring 2 points, while Player 2 scores 3 points.

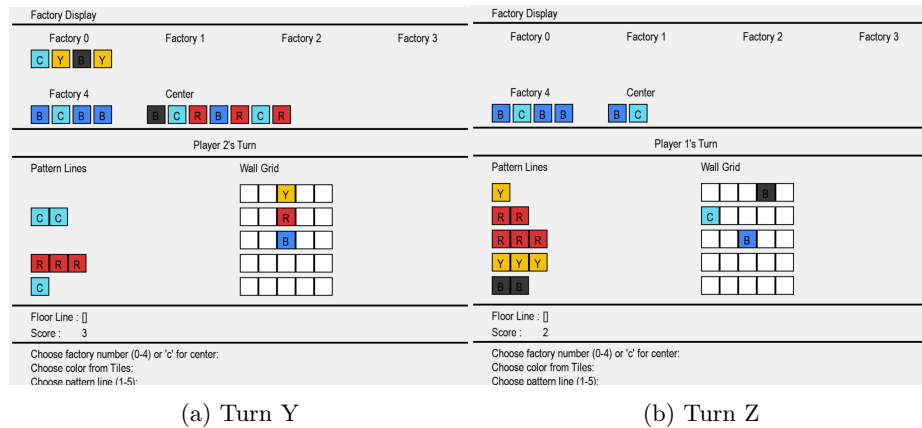


Fig. 2: Board states at different turns for Player 1 and Player 2.

6 Conclusion and Future Work

This work highlights the impact of action spaces in DRL, comparing DQN, PPO, and A2C using a custom *Azul* simulation for strategy and multi-agent interaction. Future work includes expanding the simulation and implementing and evaluating the RL algorithms.

7 Acknowledgments

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J. M. van Schalkwyk *et al.*

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Dynamic Spatio-Temporal Graph Neural Networks for Cryptocurrency Trend Classification and Change-point Detection

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Cryptocurrency market forecasting is a challenging task due to high volatility and complex stationary inter-asset dependencies. Existing forecasting models often rely on static graph structures, which fail to adapt to rapidly changing market conditions, or treat assets as independent time-series, ignoring crucial relational information. Furthermore, many deep learning models operate as “black boxes,” limiting their practical utility for risk management and strategic decision-making. This research proposes a framework based on Spatio-Temporal Graph Neural Networks (STDNNs), which model interconnected time-series data by capturing both relational dependencies and temporal patterns, to address these limitations.

We will construct dynamic graphs using time-varying correlation matrices to capture evolving cross-asset relationships over time. A key part of this study is to analyse how the STGNN model handles multiple data sources, combining internal data like price and volume with the external market volatility index to better understand overall market behaviour. To enhance transparency, the framework will incorporate explainability techniques to identify the key features, assets, and temporal

periods influencing its predictions for trend classification and change-point detection.

The proposed system's effectiveness will be evaluated against the following baseline, including Long Short-Term Memory (LSTM) networks, which process individual time-series effectively but often overlook inter-asset relationships, and Graph WaveNet(GWN), a leading technique that relies on a static graph structure. We expect this approach to yield not only improvements in predictive performance but also interpretable insights into the complex drivers of cryptocurrency market behaviour, making it a valuable tool for traders and analysts.

Deep Reinforcement Learning Applied To Stock Index Trading

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Abstract. This paper applies Deep Reinforcement Learning (DRL) to automated Stock Index trading by comparing Standard and Noisy Deep Q-Network (DQN) architectures. The trading process is formulated as a Markov Decision Process, enabling the agent to learn risk-adjusted strategies directly from market data. Using returns based rewards and Sharpe-ratio objectives, the study investigates how parameterized noise influences exploration efficiency, learning stability, and overall trading robustness.

Keywords: Reinforcement Learning · Deep Q-Network · Financial Trading · Risk-adjusted Returns

1 Introduction

Deep Reinforcement Learning provides a computational framework for solving sequential decision making problems in dynamic and uncertain environments. A DRL agent interacts with its environment by observing states, taking actions, and receiving rewards, thereby learning a policy that maximizes expected cumulative return. Formally, this interaction is modeled as a Markov Decision Process (MDP) defined by states, actions, rewards, and transition dynamics. The emergence of Deep Reinforcement Learning has enabled agents to operate in high dimensional and unstructured domains such as robotics, games, and autonomous control. However, challenges such as sample inefficiency, instability in function approximation, and the exploration–exploitation trade off remain active areas of research[1]. This study applies DRL to financial markets—highly volatile and non-stationary environments where traditional and human driven approaches often fail under uncertainty. By learning directly from market data, DRL agents can adapt trading strategies, optimize risk adjusted returns, and mitigate behavioral biases[1]. The goal of this work is to investigate the effectiveness of DRL in developing adaptive, data driven trading systems capable of achieving consistent long term profitability.

2 Literature Review

The application of Deep Reinforcement Learning to financial trading has gained substantial attention, with growing emphasis on the interplay between feature engineering, risk adjusted optimization, and model interpretability. Early studies

SM. Ratshikombo, M. Ghaziasgar

highlight the decisive role of feature design in shaping agent performance. For instance, Van Oosterhout found that overly complex momentum and volatility indicators degraded the effectiveness of DQN agents, whereas simpler, agent aware features such as trade duration enhanced policy reasoning under partial observability[3]. Extending this line of work, Wu, Xing and Chen introduced Gated DQN (GDQN) and Gated Deterministic Policy Gradient (GDPG) models incorporating Gated Recurrent Units (GRUs) to capture temporal dependencies, thereby improving resilience under volatile market conditions and underscoring the value of temporal feature extraction[7].

Recent literature has also shifted from raw return maximization toward financially meaningful, risk adjusted objectives. While early approaches relied on accuracy based metrics such as RMSE or mean returns, more recent work aligns training with financial performance indicators. Schäfer proposed a Sharpe ratio optimized framework combining Transformers and Temporal Convolutional Networks (TCNs), demonstrating enhanced performance stability[5]. Similarly, Bagheri compared risk neutral and risk averse reward functions, showing that log utility based agents achieved better capital preservation during market downturns[1]. Subsequent studies integrated Sortino ratios into adaptive DRL strategies[7] and employed distributional methods such as QR-DQN, which reduced execution costs by up to 50% relative to time weighted average price benchmarks [6]. Collectively, these works mark a transition from predictive modeling toward risk aware reward design—an essential step for institutional adoption where consistent, risk adjusted returns are paramount.

A parallel advancement concerns the integration of explainability into DRL frameworks. As trading systems grow in complexity, interpretability has become critical for regulatory compliance and user trust. De-la-Rica-Escudero introduced Explainable DRL (XDRL), integrating SHAP and LIME to provide transparency during both training and inference without significant performance loss[4]. Similarly, Mondol applied saliency maps and integrated gradients to cryptocurrency trading agents, identifying the blockchain features most influential to policy decisions. These developments reflect a broader trend toward embedding interpretability directly into DRL architectures, improving accountability and transparency in automated financial decision making[2].

Overall, the literature shows a shift from static prediction models to adaptive, risk aware, and interpretable DRL systems. The integration of robust features, risk adjusted objectives, and explainable decisions establishes DRL as a viable framework for intelligent trading in volatile markets.

3 Methodology

This study implements two Deep Q-Network architectures to evaluate the impact of exploration strategies and network stability in a financial trading environment. Both models approximate the action-value function $Q(s, a; \theta)$ through neural networks and apply the Bellman update rule:

$$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta)],$$

Deep Reinforcement Learning Applied To Stock Index Trading.

where θ^- denotes parameters of the target network periodically updated to stabilize learning. Experience replay is employed to decorrelate samples and enhance convergence.

The first setup, referred to as the **Standard DQN**, consists of a fully connected network with an input layer of 22 financial indicators, one hidden layer with 32 neurons using ReLU activation, and an output layer representing three discrete trading actions: *buy*, *sell*, and *hold*. Exploration follows an ϵ greedy policy with decaying schedules to balance exploration and exploitation.

The second setup, denoted as the **Noisy DQN**, replaces standard linear layers with parameterized noisy layers that introduce trainable Gaussian noise to the weights and biases. This approach enables intrinsic exploration by perturbing the policy directly, reducing reliance on external ϵ decay mechanisms and improving robustness against premature convergence.

Both models were trained on daily *FTSE* stock market data from 2016 to 2021 within a Gym compatible environment. Input features were stationarized using differencing, and the Augmented Dickey–Fuller (ADF) test confirmed the transformed series’ stationarity. Experience replay and periodic target network updates were used in both configurations to ensure stable training and convergence.

4 Results and Discussion

Figure 1 (left) illustrates the Sharpe ratio progression of the **Noisy DQN** architecture over 10 000 training episodes. During the initial training phase, the agent exhibits high volatility, with Sharpe ratio values fluctuating between approximately -3 and $+2$. This variability reflects the exploratory nature of the Noisy DQN, where parameterized noise promotes exploration across a wide range of trading actions.

As training progresses, these fluctuations gradually diminish. The 50 episode moving average (MA) stabilizes around a mean of 0.57, indicating that the Noisy DQN achieves **consistent positive riskv adjusted returns**. This stabilization highlights improved policy convergence and reduced overreaction to short term market noise. The smooth upward trend of the moving average confirms that the agent effectively learns to balance exploration and exploitation over time.

In contrast, Figure 1 (right) presents the performance of the **Standard DQN**. While this baseline also improves over time, its Sharpe ratio remains more erratic and converges at a lower mean value of approximately 0.24. The higher variance across episodes suggests that, without the injected parameter noise, the agent struggles to maintain stable learning dynamics and may prematurely converge to suboptimal policies.

Overall, the Noisy DQN demonstrates faster and more stable convergence compared to the Standard DQN. Its higher mean Sharpe ratio and smoother moving average indicate better adaptation to the training environment and improved robustness during the optimization process. These results suggest that

SM. Ratshikombo, M. Ghaziasgar

introducing stochasticity directly into the policy parameters enhances the learning stability and risk adjusted performance of DQN based trading agents.

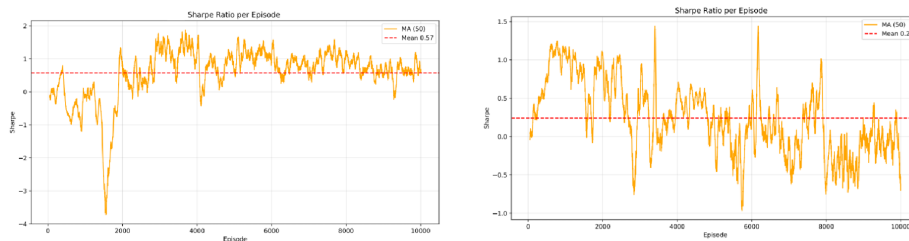


Fig. 1. Sharpe ratio of the Noisy DQN (left) and Standard DQN (right) architectures trained over 10 000 episodes.

5 Conclusion and Future Work

This study compared the **Standard DQN** and **Noisy DQN** architectures for Stock Index trading. The results showed that the Noisy DQN achieved faster convergence, greater stability, and higher Sharpe ratios during training, confirming that parameterized noise enhances exploration and prevents overfitting. In contrast, the Standard DQN exhibited unstable learning dynamics and early termination caused by severe balance drawdowns, suggesting weaker risk control and reduced adaptability in volatile environments.

The findings indicate that **noise based exploration leads to superior risk adjusted performance and learning efficiency**, offering a practical improvement for reinforcement learning applications in finance. By injecting stochasticity into network parameters, the Noisy DQN effectively maintains a balance between exploration and exploitation, producing smoother convergence and more stable policy updates. These results contribute to the growing evidence that adaptive noise mechanisms can strengthen the robustness and generalization of value based trading agents.

Future work will focus on extending this framework across diverse financial markets, including equities, commodities, and cryptocurrencies, to test generalization under varying dynamics. Rigorous testing and stress evaluation will be introduced to assess long term stability and sensitivity to transaction costs and volatility spikes. Additionally, the integration of **explainable AI (XAI)** techniques will be explored to improve policy transparency. The research will also investigate alternative **DRL models, architectures, and reward functions**—such as policy gradient methods, recurrent and transformer based agents, and Sharpe or drawdown optimized reward schemes to enhance robustness, interpretability, and real world applicability.

Deep Reinforcement Learning Applied To Stock Index Trading.

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Comparative Evaluation of Ensemble Machine Learning and Deep Learning Models for Vehicle Theft Location Prediction

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Abstract. Vehicle theft remains a major socioeconomic problem, straining households, insurers, and law enforcement agencies. Accurate forecasting of theft locations can help mitigate these losses through proactive interventions such as strategic patrols and risk-based insurance actions. Traditional risk assessment approaches typically treat theft risk as a static function of demographic and environmental attributes, overlooking the dynamic and clustered nature of theft occurrences across space and time. Such approaches, which fail to incorporate temporal and spatial dependencies, tend to offer limited predictive accuracy and reduced practical utility. To address these limitations, this study frames the vehicle theft location forecasting problem as a spatio-temporal multi-target classification problem, integrating spatial, temporal, and contextual features to capture evolving patterns of theft. Using a South African dataset, the study compared ensemble machine learning models (Random Forest, XGBoost) with deep learning approaches (LSTM, Convolutional LSTM) under a unified spatial and temporal binning framework. South Africa was divided into 20 km spatial grids, and temporal features were binned by season, day of year, and quarter. Evaluation metrics used included ranking accuracy (Top-1, Top-k), error-based metrics (MSE, RMSE, MAE), calibration metrics (Brier score), and a custom insurance oriented business metric based on the potential claim value saved. Convolutional LSTM achieved the highest strict spatial accuracy (Top-1 ≈ 0.84), followed by Random Forest (≈ 0.79), XGBoost (≈ 0.63), and LSTM (≈ 0.23). Random Forest captured the greatest potential claim value ($\approx 98\%$), ahead of Convolutional LSTM ($\approx 88\%$). The results highlight the complementary strengths of ensemble and deep learning models, and demonstrate the effectiveness of spatio-temporal modelling for forecasting vehicle theft locations.

1 Introduction

Predictive models capable of identifying high-risk areas and periods can empower vehicle owners to take preventive actions, assist law enforcement agencies in strategic deployment of patrols, and enable insurance companies to proactively manage risk exposure by advising clients on safety measures. Traditional

Khiraam Singh, Edgar Jembere, and Matthew Lee Nicholls

approaches to theft risk assessment often rely on static demographic and environmental features, treating risk as a fixed phenomenon over time and space. However, empirical evidence shows that vehicle thefts exhibit spatio-temporal clustering, with patterns that evolve dynamically, intensifying and decaying across geographic regions and time intervals; models that fail to incorporate these temporal and spatial dependencies tend to offer limited predictive accuracy and reduced practical utility [1], [2].

This study empirically evaluates and compares classical ensemble ML techniques and deep learning techniques for vehicle theft location on a South African dataset. The machine learning techniques considered were XGBoost and Random Forest, representing ensemble techniques, and LSTM and Convolutional LSTM, representing deep learning techniques. Modelling the spatio-temporal aspects of theft is addressed by binning locations and timestamps so that incidents occur within a specific spatial bin, at a specific time (the temporal bin). South Africa was split into equal-sized grids (≈ 20 km), storing the latitudes, longitudes, cities, and suburbs of every theft, and temporal bins included day of week, quarter, and day of year; this aligns with standard spatio-temporal preprocessing practices in the literature [1], [2].

2 Experimental Design

The problem solved by all models is a multi-class prediction problem where the goal is to predict the theft location (spatial bin) for a given vehicle on a given future date. All models were trained on the same chronological 70-15-15 train-validation-test split using a fixed `PredefinedSplit` to preserve temporal order. Random seeds [7, 42, 99] controlled stochasticity, and predicted probabilities from multiple seeds were aligned and averaged to reduce variance. Post-hoc spatial decoders (β, γ, λ) were tuned on the validation set and applied uniformly to all models. Evaluation was done in the same way across models using Top-1 / Top-k accuracy, MSE, RMSE, MAE, Brier score, and city-level KPIs. In this study, Top-1 accuracy refers to checking whether, for each theft incident, the model assigned the highest probability to the correct spatial bin (Top-1). Brier score gives us a comparison between predicted probabilities and actual outcomes. For the threshold-based business evaluation, an automated cutoff in [1%, 5%] maximised saved claims. The lower bound exceeded the average perbin probability ($\approx 0.76\%$) across the 131 training-seen bins, so flagged bins reflected genuine hotspots rather than background noise.

2.1 Preprocessing

Spatial binning used a grid size of $0.18^\circ (\approx 20$ km); this size was chosen because it matches the average area of postal codes in SA, which is roughly 400km^2 . The other reason for choosing this grid size was experimental, to balance the trade-off between predicting accurate spatial bins and having enough theft incidents within each bin for the model to train on. Temporal features included YEAR,

MONTH, DAY, WEEKDAY, IS WEEKEND, QUARTER, DAY OF YEAR, and SEASON, with cyclical encoding for DAY OF YEAR and WEEKDAY via sine/cosine transforms to respect periodicity; rolling features were computed at bin and city level for 1-, 7-, 14-, and 30-day windows to capture short- and medium-term dynamics without leakage, consistent with spatio-temporal feature engineering guidance [1], [2]. LSTM captured temporal dependencies in sequences [3], while ConvLSTM captured local spatial interactions that evolve over time [4].

2.2 Probability Decoding

After the classifier produced per-bin probabilities, three sequential refinements were applied with renormalisation after each step: (1) spatial smoothing by mixing each bin with the mean of its eight neighbours; (2) city-guided re-weighting using a CITY MASK to align bins with their city signal; and (3) blending with the training prior $Q = (1 - \lambda)P + \lambda \cdot \text{prior}$. Small validation sweeps around $\beta = 0.15$, $\gamma = 0.25$, and $\lambda = 0.10$ were used. This improved spatial coherence and calibration, in line with recommendations from the spatio-temporal modelling literature [1], [2].

3 Experimental Results

3.1 Evaluation of the models using traditional ML Metrics

After fitting on Validation and Training, Convolutional LSTM performed best with Top-1 = 0.844, followed by Random Forest (0.7859). XGBoost, despite higher training accuracy, obtained 0.6306 on test, indicating overfitting, and LSTM achieved 0.226. MSE/RMSE/MAE followed the same ordering (lower for better performing models). Despite a high Top-1 accuracy, Random Forest had the weakest calibration with a high multi-class Brier score (1.5957), indicating overconfidence even when the top prediction was correct.

3.2 Evaluation Metrics and Business Rule

Table 1 shows the evaluation results for the models trained in this study based on ranking accuracy (Top-1, Top-k), error-based metrics (MSE, RMSE, MAE), calibration metrics (Brier score) The Convolutional LSTM performed best with Top-1 = 0.844, followed by Random Forest (0.7859). XGBoost, despite higher training accuracy, obtained 0.6306 on test, indicating overfitting, and LSTM achieved 0.226. MSE/RMSE/MAE followed the same ordering (lower for better-performing models). Despite a high Top-1 accuracy, Random Forest had the weakest calibration with a high multiclass Brier score (1.5957), indicating overconfidence even when the top prediction was correct.

Khiraam Singh, Edgar Jembere, and Matthew Lee Nicholls

Table 1 Test set metrics for all models

Metric	XGBoost	RF	LSTM	CLSTM
Top-1	0.6306	0.7859	0.2260	0.8440
MSE	848.9482	344.3671	1082.5433	223.6407
RMSE	29.1367	18.5571	32.9020	14.9546
MAE	12.5200	5.2047	21.7163	3.7069
Brier	0.4954	1.5957	0.9349	0.3425

3.3 Business Metric: Tested on April 2024

Random Forest captured the highest potential claim value 97.9%, while ConvLSTM captured 87.8% as shown in Table 2. RF’s tree-vote averaging yields broader, smoother probability mass across neighbouring bins, which aligns with the clustered nature of thefts and benefits threshold-based scoring. ConvLSTM’s sharper, more concentrated probability peaks improve spatial precision but are less tolerant to small spatial deviations: adjacent-bin incidents can fall below the alert threshold and be counted as misses. Although RF has a higher potential claim value saved, ConvLSTM remains better calibrated and more accurate at the true-bin level [3], [4].

Table 2 Threshold-based business evaluation for April 2024.

Window	Random Forest		CLSTM	
	2024-04-01	→ 2024-04-30	2024-04-01	→ 2024-04-30
Actual incidents		55		55
Incidents inside alerted bins		49		40
Total claim value		R 8 852 495.50		R 8 852 495.50
Claim value inside alerted bins		R 8 665 503.13		R 7 775 747.08
% claim value potentially saved		97.9%		87.8%

4 Conclusion

This study evaluated whether Machine Learning or Deep Learning models perform better at vehicle theft location prediction under a unified spatiotemporal binning and evaluation framework. Convolutional LSTM outperformed every other model on strict spatial accuracy and error metrics (Top-1, MSE, RMSE, MAE) and exhibited better calibration. Random Forest achieved the highest threshold-based business capture due to a smoother probability spread across neighbouring bins; however, this caused high Brier values and therefore does not provide actionable insight. The reason for this is having limited resources, which favours placing most of it in an actual hotspot, rather than deploying a

lot of resources to prevent a few thefts. This results in ConvLSTM being able to provide more actionable insights because it is stricter in its spatial bin identification, and it can also capture the evolutionary trends through time. Future work includes larger datasets, richer temporal fields (time-of-day), alternative spatio-temporal architectures, and demographic covariates to further improve calibration and localisation [1], [2], [3], [4].

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Automated Machine Learning for Solving the Combined Algorithm Selection and Hyperparameter Optimisation Problem in Trend Prediction

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Abstract. This paper evaluates state-of-the-art multi-fidelity optimisation techniques, Bayesian Optimisation and HyperBand (BOHB) and Differential Evolution and HyperBand (DEHB), for solving the Combined Algorithm Selection and Hyperparameter Optimisation (CASH) problem in trend prediction. Critical gaps exist in trend prediction research, including the lack of empirical comparisons between state-of-the-art Deep Neural Network (DNN) architectures, particularly Temporal Convolutional Network (TCN) and Bidirectional Long Short-Term Memory (BiLSTM), and the absence of modern Automated Machine Learning (AutoML) methods. Moreover, this paper compares the performance of BOHB and DEHB when the problem search space changes from architecture-specific to the CASH search space. The novel Automated Machine Learning for Trend Prediction (AutoML4TP) platform enabled the evaluation of both optimisation techniques across multiple DNN architectures and four real-world time series. Furthermore, these findings establish empirical foundations in automated trend prediction systems across finance, meteorology, and energy sectors.

Keywords: Automated Machine Learning · Combined Algorithm Selection and Hyperparameter Optimisation · Time Series · Trend Prediction · Deep Neural Networks

1 Introduction

Time series trend prediction involves forecasting future trend slopes and durations based on historical trend patterns. DNNs have demonstrated superior performance for complex temporal time series prediction tasks [1][2], surpassing traditional statistical methods through their capacity to model non-linear dependencies in sequential data [3]. Simultaneously selecting the optimal algorithm and hyperparameter configuration requires extensive experimentation and computational resources when performed manually. This challenge is known as the CASH

A. Priscu and D. Moodley

problem [4][5]. Modern AutoML optimisation techniques automate the solving of this problem with minimal human intervention by systematically navigating combined hyperparameter configuration spaces to identify high-performing models [6]. Critical gaps exist in current trend prediction research, including the lack of empirical comparisons between state-of-the-art DNN architectures, particularly TCN and BiLSTM, and the absence of modern AutoML methods in trend prediction applications [7][8][9][10]. Notably, DEHB [11], a state-of-the-art optimisation technique that has outperformed BOHB [12] on diverse hyperparameter optimisation (HPO) problems, has never been applied to trend prediction. Furthermore, no comparison exists between BOHB and DEHB for solving the CASH problem in this context. For HPO problems, the AutoML budget allocation presents a fundamental trade-off: architecture-specific search spaces allocate the entire budget to optimising a single algorithm, while CASH search spaces distribute the same budget across multiple algorithms simultaneously [4][5], thereby reducing the number of unique configurations evaluated per DNN architecture. This paper compares the performance of BOHB and DEHB across architecture-specific and CASH search spaces, evaluating how the reduced number of unique configurations evaluated per architecture affects the final optimisation outcomes.

2 Methodology

2.1 Trend Prediction Problem Formulation

Time series are sequences of values ordered by time, where trend lines are characterised by their slope (direction and strength) and duration (length). Piecewise Linear Approximation (PLA) [13] segments time series into trend line sequences, providing a structured representation of temporal patterns. Given a historical time series and its corresponding trend sequence, the trend prediction problem aims to predict the next trend's slope and duration [8][9][10].

2.2 Experimental Design

The experimental pipeline for trend prediction progressed from data acquisition through AutoML optimisation to performance evaluation. Pre-processing comprised missing data imputation, smoothing, PLA trend segmentation, and sliding window operations to form input-output data instances. Four real-world time series were utilised: CT Temp (Cape Town weather forecasting), JSE (Johannesburg stock pricing), Methane (sensor readings), and Voltage (household power consumption). Five DNN architectures were compared on each time series: Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), TCN, Long Short-Term Memory (LSTM), and BiLSTM, each with individually defined hyperparameter search spaces [7]. For predicting trends, the input features combined local point data with historical trend lines. Furthermore, the experiments were conducted using the AutoML4TP platform, which was developed for

AutoML for Solving the CASH Problem in Trend Prediction

this research. This novel platform democratises access to modern DNNs, enabling non-experts to obtain high-performing models for trend prediction with minimal manual intervention. Within this platform, the AutoML optimisation techniques automated DNN architecture selection and HPO through iterative candidate configuration evaluations. Model evaluation employed walk-forward validation [14], which preserved temporal dependencies through successive and overlapping partitions with a 4:1:1 ratio for training, validation, and test sets. In addition, model stability was incorporated through multiple candidate configuration evaluations with the standard deviation penalty added to mean validation Root Mean Squared Error (RMSE). For each time series, the final optimal AutoML model was independently evaluated ten times. For robustness, each experiment was run ten times and each configuration was evaluated across three walk-forward validation iterations [8]. Two primary AutoML budget allocations were compared. Architecture-specific search spaces dedicated all 60 AutoML iterations to optimising a single architecture, enabling more unique configurations per architecture. Conversely, the complete CASH search space allocated the same 60 iterations across all five architectures simultaneously, evaluating fewer configurations per individual architecture but exploring the entire algorithm space [4][5]. Both BOHB and DEHB are hybrid multi-fidelity optimisation techniques. BOHB combines HyperBand [15] with Bayesian Optimisation [16], whereas DEHB combines it with Differential Evolution [17]. Both of these techniques use adaptive resource allocation strategies to identify high-performing configurations within a given AutoML budget. Thus, the techniques utilised minimum and maximum epoch budgets of 100 and 400, respectively, with their eta parameter set to two, enabling three epoch budget levels [11][12]. Finally, performance was assessed through Average RMSE (equally weighted slope and duration predictions) and trend direction classification accuracy. Percentage improvement was calculated when transitioning from architecture-specific to CASH search space.

3 Results and Discussion

Table 1 presents the performance comparison of BOHB and DEHB across both search spaces, with percentage improvement calculated for CASH search space performance relative to architecture-specific baselines.

Fig. 1 illustrates the Average RMSE distributions of BOHB versus DEHB across ten runs for CT Temp, JSE, Methane, and Voltage, with diamond markers indicating the best architecture-specific model performance.

3.1 Overall Search Space Comparison

In Table 1, five of the eight test cases showed that models from the CASH search space matched or outperformed architecture-specific counterparts. DEHB achieved improvements in three of four time series when transitioning to the CASH search space, whereas BOHB improved in two of four. Both techniques maintained strong anytime performance despite evaluating fewer configurations per architecture, confirming their scalability to higher-dimensional search spaces.

A. Priscu and D. Moodley

Table 1. Performance Comparison of BOHB and DEHB in Architecture-Specific and CASH Search Spaces

Time Series	Search Space	BOHB			DEHB		
		Average RMSE	Accuracy (%)	Algorithm	Average RMSE	Accuracy (%)	Algorithm
CT Temp	DNN	13.28 ± 0.560	89.286 ± 3.571	BiLSTM	13.402 ± 0.424	90.714 ± 2.906	BiLSTM
	CASH	13.532 ± 0.653	90.0 ± 5.303	LSTM	13.909 ± 0.356	91.429 ± 2.182	TCN
	% Improvement	-1.9	0.8	-	-3.78	0.79	-
JSE	DNN	8.713 ± 0.042	51.321 ± 4.476	BiLSTM	8.701 ± 0.105	52.704 ± 2.934	TCN
	CASH	8.46 ± 0.072	54.717 ± 3.304	TCN	8.587 ± 0.096	54.78 ± 1.789	TCN
	% Improvement	2.9	6.62	-	1.31	3.94	-
Methane	DNN	130.466 ± 3.373	53.485 ± 1.767	TCN	132.628 ± 4.477	54.47 ± 1.775	TCN
	CASH	138.705 ± 3.871	54.697 ± 1.259	TCN	130.569 ± 2.751	54.697 ± 1.754	TCN
	% Improvement	-6.32	2.27	-	1.55	0.42	-
Voltage	DNN	8.99 ± 0.033	77.708 ± 0.823	TCN	8.847 ± 0.059	77.695 ± 0.426	MLP
	CASH	8.903 ± 0.058	77.249 ± 0.454	CNN	8.758 ± 0.086	77.398 ± 0.675	CNN
	% Improvement	0.97	-0.59	-	1.01	-0.38	-

3.2 BOHB vs DEHB Optimisation Characteristics

As illustrated in Fig. 1, BOHB exhibited wider interquartile ranges, indicating greater variability between runs. Despite this, BOHB occasionally identified marginally superior individual model configurations, particularly on JSE. This performance came at the cost of higher uncertainty across multiple runs. In contrast, DEHB demonstrated narrower distributions, evidencing superior consistency in identifying high-performing configurations. In addition, DEHB achieved better median performance across all the time series except JSE. Thus, DEHB is more suitable for applications requiring predictable performance across runs, while BOHB remains viable when seeking potentially superior individual models despite greater uncertainty.

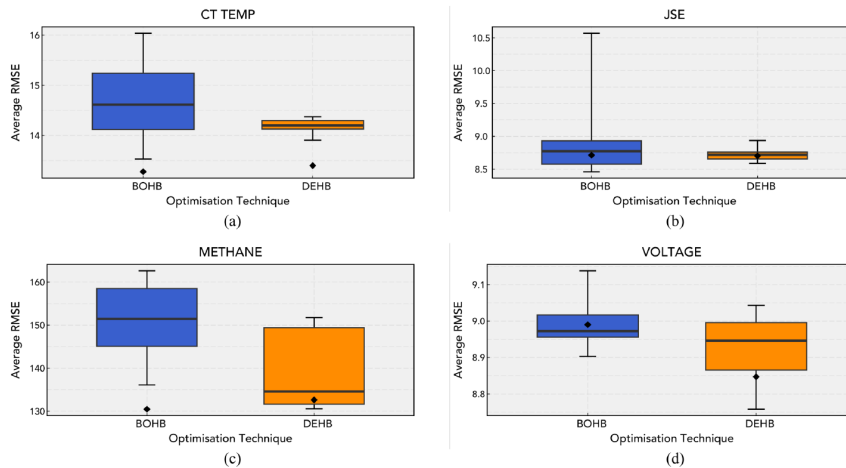


Fig. 1 Average RMSE distributions of BOHB and DEHB across ten runs in the CASH search space for (a) CT Temp, (b) JSE, (c) Methane, and (d) Voltage.

3.3 Architecture Preferences

From 80 total runs, the TCN and CNN dominated the CASH search space results with 40 and 28 identifications, respectively. In contrast, the BiLSTM and LSTM were underutilised with only three and one identifications, respectively, reflecting the curse of dimensionality in complex architectures [18]. When the AutoML budget is distributed across the CASH search space, reduced unique configurations per architecture proved insufficient to explore this high-dimensional search space thoroughly. Simpler architectures like the CNN were explored more thoroughly because their compact search spaces require fewer evaluations to cover adequately, increasing the likelihood of identifying near-optimal configurations within the limited budget [7][8]. Architecture preferences remained consistent across both optimisation techniques. In architecture-specific search spaces with sufficient evaluations, modern architectures demonstrated superior performance: BiLSTM achieved optimal results on CT Temp, while TCN outperformed all architectures on JSE, Methane, and Voltage.

4 Conclusion

This paper demonstrates that CASH search spaces offer valuable architectural diversity when the optimal architecture is unknown. Despite evaluating fewer configurations per architecture, the CASH space achieved competitive performance by escaping local optima through architecture switching, a strategy unavailable to architecture-specific search spaces. However, practitioners must recognise that this exploration- exploitation trade-off naturally favours algorithms with compact hyperparameter spaces. This potentially introduces bias against complex architectures that might excel given adequate exploration. Future research should further investigate optimisation techniques that are scalable to high-dimensional search spaces, enabling more exploration across architectures of varying complexity. Overall, DEHB demonstrated advantages in navigating the higher-dimensional CASH search space, thereby establishing it as the preferred technique for real-world applications that prioritise cross-run consistency. However, BOHB occasionally identified model configurations that resulted in superior individual performance, which may benefit research contexts that prioritise single-run optimisation performance. These findings establish empirical foundations for informed AutoML deployment in automated trend prediction systems.

Disclosure of interests

The authors have no competing interests to declare that are relevant to the content of this paper.

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ChatGPT-Enhanced Suicide Risk Annotation: A Hybrid LLM-Human Framework for Social Media Data

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Abstract. Detecting suicide risks using social media data remains a challenge in mental-health research. While machine learning models can identify linguistic markers of distress, their success depends on high-quality labelled data, a process that is often subjective, time-consuming, labour-intensive, and emotionally demanding. This study presents a hybrid human-AI annotation framework that uses ChatGPT-5 as a co-annotator alongside human reviewers to classify Reddit posts based on the Columbia-Suicide Severity Rating Scale (C-SSRS). The hybrid approach increased annotation efficiency by 357%. ChatGPT-5 demonstrated contextual sensitivity to sarcasm, idiomatic expressions, and urgency cues, with misclassifications in metaphorical language corrected through human oversight. This approach enhances efficiency in preparing data from Reddit posts for suicide risk assessment, contributing to the broader agenda of responsible AI. The labelled dataset supports scalable and reproducible research for early warning and decision support systems in mental health care.

Keywords: Transparency, Hybrid Annotation, Large Language Models, Social Media Data, Suicide Risk Assessment.

1 Introduction

Suicide is a critical public health challenge and a leading cause of premature mortality, with particularly high rates reported among young people and specific demographic groups [1]. Many individuals disclose suicidal thoughts online before seeking formal help, making online platforms such as Reddit or Twitter (now X) important for early suicidal-warning systems [2, 3]. Subreddits such as *r/SuicideWatch* offer unfiltered

T. Mokheleli et al.

narratives of emotional distress [4], yet transforming such content into structured data suitable for computational analysis presents ethical and methodological challenges [2]. To address these challenges, researchers introduce a human-labelled ground-truth layer to make the data usable for supervised approaches [5]. This often entails assigning labels to posts retrieved from online platforms, a process commonly known as manual annotation. Although this process is important for supervised machine learning (ML) [6], it is, however, slow and psychologically demanding [6], especially in this domain. Annotators must interpret diverse linguistic cues, from explicit self-harm declarations to subtle expressions of hopelessness, often written in non-standard forms, for example, “*I’m gonna kms*” = “*I am going to kill myself.*” At the same time, the recent emergence of Large Language Models (LLMs) presents new opportunities for automating certain aspects of this process while maintaining human oversight [7].

This study explored how ChatGPT-5 can enhance human annotations by offering hybrid co-labelling guidance, informed by clinically validated scales such as the Columbia-Suicide Severity Rating Scale [8]. The aim is not to replace human expertise but to improve the efficiency and quality of the annotation process while reducing the emotional strain associated with analysing suicide-related posts. By embedding transparency and human review, this study contributes to the growing discourse on responsible AI for mental health research.

2 Methodology

2.1 Data Extraction from Reddit

User-generated posts were collected from the subreddit *r/SuicideWatch* in August 2025 using the Asyncpraw Python wrapper for Reddit’s application programming interface. Authentication credentials (Client ID, Secret, User Agent) were securely configured in accordance with Reddit’s developer protocols [9].

Metadata captured included: *post_id*, *title*, *selftext*, *num_comments* and *created_utc*. After deduplication based on *post_id* and concatenation of *title* and *selftext* fields, the final dataset comprised 1,910 unique posts.

2.2 Annotation Schema

Each post was categorised into five C-SSRS-aligned categories (Table 1):

Table 1. Annotation schema for Reddit posts (adopted from [8])

Level	Label	Definition
0	Not relevant	Unrelated to mental health or emotion
1	Emotional distress	Negative affect (sadness, hopelessness) without suicidal reference
2	Suicidal ideation	Desire to die, no method specified
3	Suicide planning	Reference to the method or preparations
4	Imminent risk	Immediate intent or ongoing attempt

2.3 Human Annotation

An initial annotator labelled 16% of the posts manually over seven to eight days. Four additional annotators independently labelled the same subset (blind to prior labels) to assess reliability. Posts were distributed evenly, and annotators worked in short sessions to minimise fatigue and exposure to second-hand trauma. The agreement exceeded 84%, with disagreements found in neighbouring classes such as *suicide planning* and *imminent risk*. Consensus resolution produced the gold-standard labels [10].

2.4 LLM-Assisted Validation

The study introduced ChatGPT-5 as an artificial intelligence (AI) co-annotator for assessing suicide risk. To standardise the process, human annotators created a dedicated ChatGPT Project, using the Add Files feature to incorporate the C-SSRS schema and a structured instructional template. This enabled the model to reference the authoritative assessment criteria continuously throughout the analysis.

By prompting the AI with a structured input, the system generated outputs comprising the specific suicide risk level label and a methodologically transparent rationale, thereby enhancing the efficiency and reproducibility of the annotation process while strictly adhering to the established clinical metrics from the C-SSRS schema. Human reviewers cross-checked the AI's rationales against their own manual annotation decisions for the initial 300 posts. If the AI's justification aligned with the human decision, confidence in that annotation increased. Whenever discrepancies occurred, human decision prevailed, enforcing a strict human-in-the-loop ethical methodology [11]. This dual-layer process minimised doubt and resulted in a validated dataset.

2.5 Emotional Safeguards

Given the sensitivity of suicide-related material, to mitigate potential emotional fatigue and maintain consistency, a strict procedural rule was implemented: annotators were limited to processing less than 30 posts per sitting and not more than 100 per day, with the precise quota adjusted based on the length and density of the textual content.

3 Results

The hybrid approach significantly improved annotation efficiency, with the number of labelled posts approximately 357% higher compared to manual annotation. While manual annotation of 300 posts (16% of the dataset) required seven days, the hybrid method completed all 1,910 posts in just nine days. This gain was achieved while maintaining stable inter-annotator consistency.

ChatGPT-5 effectively recognised contextual cues such as sarcasm, idiomatic expressions (“end it all,” “I’m done”), and time-based urgency. However, in some cases, it misclassified posts containing metaphorical language, often confusing figurative expressions with literal suicidal intent. These errors were consistently corrected during

T. Mokheleli et al.

the human-in-the-loop validation stage. Although all annotations were done in one ChatGPT project, long runs of 80–100 posts at once occasionally led to contextual drift, where the model produced mild hallucinations and responses that were coherent but inconsistent with the predefined labelling schema. To minimise these errors, the posts were divided into smaller batches, and ChatGPT-5 was restarted for each batch so it could evaluate each post independently and according to the labelling schema.

4 Discussion

The findings demonstrate that integrating ChatGPT-5 as a co-annotator improved efficiency without compromising accuracy, aligning with prior studies that highlight the value of hybrid human-AI workflows in sensitive text analysis tasks [7]. The model's ability to recognise contextual cues such as sarcasm and idiomatic expressions supports existing evidence that large language models can interpret informal online language with reasonable contextual understanding [12]. However, occasional misclassifications of metaphorical expressions show the continuing need for human oversight and domain sensitivity in suicide-related annotation.

This study contributes to responsible AI by using a transparent, human-in-the-loop annotation process that ensures interpretability, traceability, and ethical accountability. The hybrid framework shows how generative AI can augment, rather than replace, human judgment in high-risk mental health research. The labelled dataset also provides a foundation for explainable and reproducible ML applications, supporting theoretical advances in digital phenotyping and practical development of early-warning and decision-support systems. Beyond the Reddit dataset, the framework can be extended to similar domains, such as counselling transcripts and clinical records, illustrating its scalability for future data-driven mental health interventions.

5 Limitations and Future Work

Although the framework achieved consistent labelling and improved efficiency, limitations include its reliance on English-language posts and the need for manual verification of ambiguous or metaphorical expressions. The process also depends on careful prompt engineering and requires moderate computational costs during large-scale validation. Future work should address these limitations by incorporating multilingual and domain-specific embeddings, refining prompt strategies to reduce costs, and testing generalisability on alternative datasets.

6 Conclusion

This study presents a reproducible, ethically grounded framework for hybrid suicide-risk annotation that uses ChatGPT-5 to support human annotators. By combining clinical validity (C-SSRS), social-media contextual sensitivity, and transparency, the approach enhances efficiency while preserving human oversight. The broader

ChatGPT-Enhanced Suicide Risk Annotation

significance lies in demonstrating that hybrid human-LLM collaboration can serve as a bridge between tireless manual annotation and ethical responsibility, paving the way for scalable, trustworthy, and responsible AI in mental health research.

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Regulating AI Through Digital Strategy Collective Agreements

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As artificial intelligence (AI) systems rapidly integrate into workplaces and reshape decision-making, traditional regulatory mechanisms often reactive and legalistic, are proving insufficient to address the ethical, labour, and governance challenges arising from digital transformation. These include concerns around algorithmic bias, opaque decision-making, worker displacement, data rights, and accountability in high-risk sectors. The urgency lies in developing governance models that are not only legally robust but also participatory, adaptive, and grounded in the realities of evolving work relations.

This work introduces the concept of Digital Strategy Collective Agreements (DSCAs) as an innovative, agile, and context-sensitive form of AI governance. Building on established traditions of collective bargaining, DSCAs function at both workplace and sectoral levels to provide structured, negotiated guidelines for

digital adoption. They embed worker rights, transparency, and accountability into organisational strategies, while enabling employers and trade unions to proactively negotiate on issues such as algorithmic decision-making, job redesign, digital skill development, and responsible data use. Unlike rigid legal instruments that struggle to keep pace with technological change, DSCAs offer a flexible yet enforceable framework that complements formal regulation while fostering trust between stakeholders.

For businesses, DSCAs represent a proactive risk management and compliance mechanism, aligning AI adoption with global regulatory standards (e.g., EU AI Act, OECD, ISO, POPIA, and constitutional labour protections in South Africa). For policymakers, DSCAs provide a bottom-up model of regulatory innovation, demonstrating how participatory governance can mitigate risks while promoting inclusive and sustainable digital transformation. For academics and researchers, DSCAs open a new line of inquiry into how labour institutions can evolve to govern AI, and how negotiated frameworks can support both organisational agility and social justice in the digital economy.

This work presents insights into the theoretical foundations, practical design, and cross-sector applicability of DSCAs. Case scenarios will illustrate how DSCAs can function in different industries, including health, finance, and ICT, providing lessons for

both advanced economies and developing contexts. By positioning collective agreements as a strategic governance tool for digitalisation, the presentation argues that DSCAs hold the potential to bridge gaps between law, policy, and practice, ensuring that AI-driven transformation remains fair, accountable, and human-centred.

AI Literacy for Learners in Low-Income Communities: Co-designing with Educators and Learners in Youth Organisation within South Africa

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The integration of Artificial Intelligence (AI) into everyday life is advancing at an unprecedented pace, significantly shaping individuals and societies. Young learners are growing up in environments increasingly influenced by intelligent systems, making early AI literacy essential for developing critical understanding and informed engagement. While AI literacy studies have sought to empower learners in understanding, engaging, creating, and evaluating AI, young learners from low-income communities in South Africa remain under-represented. These communities face unique challenges, shaped by sociocultural values, lived experiences, and educational realities. In addition, many existing studies overlook the inclusion of both learners and educators as

equal design partners in the design process, despite their unique insights and contextual needs. Learners and educators have unique needs, especially in developing contexts and including them in the design process reveals their behaviours and enables them to voice their opinions and perspectives in shaping designs.

This study addresses this gap by exploring learning strategies towards co-developing AI literacy learning toolkits with learners and educators in youth organisations within low-income South African communities. Adopting a community-based co-design approach, the study positions learners and educators as equal design partners throughout the design process. Data will be gathered through interviews and co-design workshops, followed by qualitative analysis to identify design requirements and effective learning strategies.

The anticipated outcomes include a deeper understanding of learning strategies when designing “with” and “for” learners and educators in African contexts, and the development of AI literacy learning toolkits tailored to learners in low-income South African communities. By fostering AI literacy in these communities, this research will contribute to the broader discourse on AI literacy and provide insights to inform future decision-making around equitable AI education.

Algorithms and Problem Domains for Fully Quantum Machine Learning

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This project starts with an analysis of existing quantum machine learning optimization techniques in order to explore directions beyond hybrid classical-quantum approaches and investigate emerging ideas for fully quantum methods. Extending current approaches, this project investigates potential learning models that operate entirely within a quantum framework, without relying on classical optimization or hybrid training routines.

An initial hypothesis is that discrete quantum structures such as quantum oracles, amplitude amplification, quantum walk, and measurement-based selection could be used to define learning procedures in place of conventional loss functions. These non-variational methods are especially well-suited for structured, low-data, or rule-based tasks and may provide a potential pathway toward fully quantum alternatives to variational approaches.

While non-variational approaches represent one class of alternative frameworks considered in this project, the research remains open to exploring additional approaches as potential pathways toward fully quantum machine learning. This includes identifying problem types to which these techniques may be applicable, and exploring the possibility of constructing fully quantum learning models. The project will involve both theoretical investigations and practical circuit design and simulation.

The VR-AI-Assisted Power Grid Management Education

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Virtual reality (VR) has transformed classical education and training, especially over the past decades. This study introduces PowerGrid VR, a VR-based, AI augmented educational program. The core of PowerGrid VR is to simulate a power grid environment, allowing users, such as power grid management trainees to interact with VR control panel and receive feedback through data-driven algorithms powered by machine learning agent (Unity).

The simulation incorporates historical power distribution data and AI-based decision-making algorithms to guide trainees to experience complex power management systems. In addition to training, this project explores Unity AI tools such as behaviour trees and reinforcement learning agent to simulate decision-making strategies in power grid management. This study is situated at the intersection of AI, immersive technology and sustainable energy

management. PowerGrid VR interdisciplinary AI study that combines simulation design, machine learning and public education.

This project demonstrates that AI-powered virtual environments can serve as training tools and public engagement platform to address the socio-technical challenges of resource management.

STGNN for Trend Line Prediction on the JSE

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This study explores the use of Spatial-Temporal Graph Neural Networks (STGNNs) for predicting stock trend lines and detecting trend change points on the Johannesburg Stock Exchange (JSE). It investigates how temporal and structural dependencies among stocks can improve trend prediction accuracy and interpretability.

Baseline experiments compare deep models: Long Short-Term Memory (LSTM) and Temporal Convolutional Networks (TCN), with the graph-based baseline, Graph WaveNet (GWN).

The models predict trend slope and duration targets derived from close prices. Results show that TCN and GWN outperform LSTM on sMAPE while achieving comparable RMSE. Incorporating trend-oriented features further enhances slope stability and realism, laying the groundwork for applying advanced STGNN architectures to financial trend prediction.

Learning Dynamic Dependencies in Spatial-Temporal Systems for Efficient Forecasting

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Cryptocurrency market forecasting is a challenging task due to high volatility and complex stationary inter-asset dependencies. Existing forecasting models often rely on static graph structures, which fail to adapt to rapidly changing market conditions, or treat assets as independent time-series, ignoring crucial relational information. Furthermore, many deep learning models operate as “black boxes,” limiting their practical utility for risk management and strategic decision-making. This research proposes a framework based on Spatio-Temporal Graph Neural Networks (STDNNs), which model interconnected time-series data by capturing both relational dependencies and temporal patterns, to address these limitations.

We will construct dynamic graphs using time-varying correlation matrices to capture evolving cross-asset relationships

over time. A key part of this study is to analyse how the STGNN model handles multiple data sources, combining internal data like price and volume with the external market volatility index to better understand overall market behaviour. To enhance transparency, the framework will incorporate explainability techniques to identify the key features, assets, and temporal periods influencing its predictions for trend classification and change-point detection.

The proposed system's effectiveness will be evaluated against the following baseline, including Long Short-Term Memory (LSTM) networks, which process individual time-series effectively but often overlook inter-asset relationships, and Graph WaveNet(GWN), a leading technique that relies on a static graph structure. We expect this approach to yield not only improvements in predictive performance but also interpretable insights into the complex drivers of cryptocurrency market behaviour, making it a valuable tool for traders and analysts.

Local Social Structures as Enablers and Barriers for AI Enabled Medical Drone Delivery: Early Evidence from a Developing Economy

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Medical Drone Delivery Systems (MDDS) such as Zipline in Rwanda has become an innovative solution to address healthcare supply challenges in developing economies (Ackerman & Koziol, 2019). MDDS employ Artificial Intelligence (AI) for autonomous flight and route optimisation, yet their long-term operational sustainability is seldom studied mostly in relation to local social structures that enable or constrain success.

Using semi-structured interviews and document analysis, this multi-method qualitative study examines how community trust, governance norms, and regulatory frameworks shape the operational sustainability of MDDS. Findings reveal strong public trust in government as a key social enabler, while technical

constraints such as 3 kg payload limits and strict airspace regulations act as barriers.

The work is grounded in an interpretivist stance, further grounded in Structuration Theory (Giddens, 1984) and a sociomaterial perspective (Leonardi, 2011; Holeman & Barrett, 2017) to explain how material affordances and social structures interact in practice. The study contributes early empirical evidence on the socio-technical dynamics of AI-enabled drone logistics and offers actionable insights for policymakers seeking to integrate MDDS into national healthcare systems.

Network Intrusion Detection Datasets: A Systematic Literature Review

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Network intrusion detection systems (NIDSs) have been used to secure networks from cyber attacks in different organisations. Various studies have demonstrated the use of network traffic datasets in validating machine learning-based NIDS models by detecting network intrusions. Networks and cyber attacks are becoming complex due to the advancement of technology, with this problem being compounded by an increase in the number of users and devices.

As technology advances, network security experts must incorporate the new datasets in the model's development to reflect the real network environments. Therefore, this study used the Preferred Reporting Items for Systematic reviews and Meta Analysis (PRISMA) framework to conduct a systematic literature review and to summarize 71 studies published between January 2022 and February 2025.

The study found that the datasets used at least five times are CICIDS2017, UNSW-NB15, NSL-KDD, CICIDS2018, CSE-CICIDS2018, CICDDoS2019 and KDDcup1999. Finally, the study showed the need for researchers to contribute new network datasets to reflect the real network environment.

Index of Authors

Adongo, Ephraim Awinzoya, 69

Baker, Clayton, 67
Bokaba, Tebogo, 53

Chasi, Dionne Takudzwa, 23
Choi, Dukyung, 67

de Laroche Souvestre, Laurent, 67

Gasant, Mujahid, 27
Ghaziasgar, Mehrdad, 27, 35

Isingizwe, Jean Frederic, 9

Jameel, Moegamad, 65
Jembere, Edgar, 41

Klein, Ashwil, 9

Maharaj, Ahana, 15
Mnguni, Vusi, 59
Moges, Henok Tenaw, 71
Mokheleli, Tsholofelo, 53
Moodley, Deshendran, 3, 15, 23, 33, 47, 69
Mphahlele, Tharollo, 9
Mudau, Rovhona, 19

Mutembei, Leonard, 75

Ndayishimiye, Evode, 73
Ndayizigamiye, Patrick, 53
Ndlovu, Nompumelelo, 53
Ngcobo, Luvuyo, 1
Nicholls, Matthew Lee, 41
Nyadzayo, Mazwi Kelvin, 33

Oluwatuyi, Rachel, 63

Priscu, Alex, 47

Radovanovic, Aleksandar, 65
Ratshikombo, Sedzani Meshak, 35

Singh, Khiraam, 41

Twinomurinzi, Hossana, 53

Uys, Walter, 73

van Schalkwyk, Jené Mercia, 27
van Schalkwyk, Roelof, 3

Weimann, Edda, 73