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Crime Forecasting Using a Hybrid BiGRU–Transformer Neural Architecture: A Deep Learning Approach on Austin Crime Data

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Revanth Reddy Mallidi
Student ID: 23408308

School of Computing
National College of Ireland

Supervisor: Dr. Muhammad Asif Razzaq

National College of Ireland

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Crime Forecasting Using a Hybrid BiGRU–Transformer Neural Architecture: A Deep Learning Approach on Austin Crime Data

Revanth Reddy Mallidi

23408308

Abstract

Crime forecasting has become increasingly important as urban environments generate large volumes of dynamic, irregular, and non-linear crime data that traditional statistical models struggle to interpret. With cities trusting on data analytics to improve public safety there is a pressing need for models that can capture long-term dependencies, sudden spikes and complex behavioural trends in crime patterns. This study addresses this gap by developing a novel Hybrid BiGRU–Transformer (BiGRU-MHSA) approach which has designed to enhance predictive accuracy and inference performance in time-series crime forecasting. Using a large-scale dataset from the Austin Police Department, the research applies systematic data preprocessing, feature engineering, 15-day rolling window sequence generation, and comparative experimentation across LSTM, MLP, GRU, BiGRU, and the proposed hybrid model. Results show that the BiGRU-MHSA significantly reduces prediction error MSE 7.289, MAE 2.131 and offers an optimal balance between accuracy and computational efficiency. The model advances the state of the art by combining bidirectional temporal learning with multi-head attention, enabling more context-aware and stable predictions than traditional deep learning baselines. In practice, this provides law-enforcement agencies with a more reliable and real-time tool for proactive resource allocation. However, challenges remain in addressing data noise, district-level variability, and the need for adaptive learning in evolving crime environments.

Keywords: Crime Forecasting, Time-Series Analysis, BiGRU–Transformer Model, Deep Learning, Predictive Analytics

1 Introduction

This chapter introduces the background of crime forecasting, explains the importance of using advanced deep learning models for improving prediction accuracy, and presents the research question and objectives.

1.1 Background

The field of data analytics has become a vital field that converts the raw data into meaningful information through the systematic process of data collection, cleaning, exploration, modelling, and interpretation. Crime forecasting is a use of data science, which has grown to become an indispensable tool (Alshahrani and Khanzada, 2025) as cities become more dependent on digital records to comprehend and deal with the personal security issues. Crime is a spatiotemporal event in nature that implies that its patterns change over time and differs across various geographical regions (Mao et al., 2025). Conventional descriptive statistics or historical trends have traditionally been used by the police departments in predicting criminal activity but they are poor in reflecting nonlinear behaviours, seasonality and abrupt changes. Due to the development of machine learning and deep learning, time-series forecasting has become a leading trend, allowing models to adapt (Dao et al., 2024) to the long-term dependencies and latent trends of crime data. RNNs, LSTMs, and GRUs have been found to be effective in sequence modelling, and new architectures like Transformers and attention mechanisms are also useful in improving representation learning by emphasizing the most important aspects of a sequence. Hybrid deep learning models represent one of the promising directions as crime data grows bigger and more intricate, and the accuracy of prediction and the possibility of using data to make decisions for the agencies can be enhanced.

1.2 Importance of the Study

The importance of this study lies in its contribution to enhancing the accuracy, efficiency, and reliability of crime forecasting systems by integrating a hybrid BiGRU–Transformer deep learning architecture. Since urban crime trends become more complex and dynamic, the classical statistical and independent deep learning models are frequently unable to maintain the long-term temporal relations, abrupt changes, as well as the relationships existing among contexts in crime data. This study fills this gap by taking advantage of the use of more advanced sequence-learning and attention mechanisms to generate more accurate predictions which can be utilized in proactive policing and resource allocation. Enhanced prediction assists law-enforcement agencies to predict hotspots, plan patrols more optimally and respond faster, which eventually results in safer communities. Moreover, the research employs extensive real-life data of the Austin Police Department, which supports its practical usefulness. The study provides a reliable and operationally feasible method of predicting crime in real-time in current smart-city systems by considering the predictive efficacy and inference efficiency of the models.

1.3 Research Question

How does a hybrid BiGRU–Transformer model influence error reduction and inference efficiency in time-series crime prediction compared to traditional deep learning architectures?

1.4 Research Objectives

This study is having three main objectives which includes:

1. To develop and implement multiple deep learning baseline models (LSTM, MLP, GRU, BiGRU) for time-series crime forecasting and evaluate their predictive accuracy using metrics such as MSE, RMSE, and MAE.
2. To design a hybrid BiGRU–Transformer (Multi-Head Self-Attention) architecture and investigate its ability to capture long-term temporal dependencies and contextual crime patterns more effectively than traditional sequential models.
3. To conduct a comprehensive comparative assessment of all models based on predictive performance, inference latency, and throughput, in order to determine whether the proposed hybrid BiGRU–Transformer model delivers a significant improvement in both error reduction and computational efficiency for real-time crime forecasting.

1.5 Structure of the Study

This study is having structure of the report which includes:

1. **Chapter 1 Introduction**: Introduces the background of crime forecasting, explains its importance, and clearly states the research question, objectives, and structure of the study.
2. **Chapter 2 Related Work:** Reviews existing research on crime prediction, deep learning models, and transformer-based approaches, summarising prior methods, results, and limitations, and identifying gaps relevant to this study.
3. **Chapter 3 Methodology:** Describes the dataset, preprocessing steps, exploratory data analysis, feature engineering, scaling, and the rolling-window sequence generation process used for time-series crime forecasting.
4. **Chapter 4 Design Specification:** Presents the system architecture and provides justification for the proposed hybrid BiGRU–Transformer model.
5. **Chapter 5 Implementation:** Details the technology stack and explains how each model (LSTM, MLP, GRU, BiGRU, and BiGRU-Transformer) was built, trained, configured, and regularised.
6. **Chapter 6 Evaluation:** Evaluates all models through actual-vs-predicted comparisons, performance metrics (MSE, RMSE, MAE), and computational efficiency analysis covering latency and throughput.
7. **Chapter 7 Conclusion and Future Work:** Summarises the findings, highlights limitations, and outlines directions for extending the study in future research

2 Related Work

This chapter reviews existing research on crime prediction in smart cities, summarises prior work on deep learning and transformer-based approaches, highlighting their architectures, results, and limitations across crime forecasting, intent detection, and legal judgment analysis.

2.1 Crime Prediction and Forecasting in Smart Cities

Crime forecasting has become a vital part of the current intelligent city ecosystem in which policing policies, resource mobilisation, and community safety (Sarker, 2022) will be informed by data-driven insights (Springs, 2024). Due to the increasing complexity of urban environments, crime patterns are heavily dependent on time and space in relation to population density, socioeconomic context, seasonal changes (Dao et al., 2024), and neighbourhood interactions (Onyeneke and Karam, 2022). Manual and statistical methods of traditional value trend analysis, ARIMA, or hotspot mapping provide valuable descriptive information but they fail when the behaviour of crimes becomes highly non-linear, irregular, or dynamic. In addition, these traditional methods usually presuppose stationarity and the inability to capture long-term relationships, event-specific variations or interactions between different types of crimes. As the availability of open police information has increased, scientists have turned to predictive models that are able to learn the latent temporal regularities and crime dynamics. Time-series forecasting has turned out to be a promising tool that enables crime departments to forecast when incidents are most likely to occur and when the situation is at its most risky, allowing for the prevention of new trends (Keatley and Clarke, 2022). Nonetheless, the nature of urban crime is noisy, periodic, and irregularly diffused geographically, and simple modes can hardly be used to describe such complexities. These constraints discuss the necessity of higher-level deep learning techniques that are capable of capturing the sequential relationships, responding to the changing patterns and providing high-quality forecasts in real-time smart-city policing situations.

2.2 Deep Learning and Transformer-Based Forecasting

The recent development of deep learning and transformer architectures has further enhanced crime forecasting by reducing the limitations of the traditional statistical and machine learning models. The wide range of study includes neural networks to autoregressive transformers which shows how the modern methods of AI can be used to improve the accuracy, interpretability, and real-time analysis in various fields related to crime. First study given by (B Ikwen et al., 2024) proposed a Multi-Layer Perceptron (MLP) architecture that was trained on 4,748 police records, which showed good predictive performance (accuracy 74% F1-score 0.79) and presented the possibility of using neural networks to predict crime hotspots, but was limited in its scalability by the quantity of data and its extrapolation. (Sathya and Fernandez, 2023) was able to broaden the use of MLPs through the suggested ontology-based MLP classifier to identify criminal intent on social media and was able to successfully combine domain-specific slang with neural feature-selling; however, there were challenges due to changing language trends and maintenance of ontology. The studies given by (Vardhan and Chandar, 2025a) and (Vardhan and Chandar, 2025b) have further compared MLPs with classical models like Decision Trees, Naive Bayes in predicting road-crime where MLP was found to be always more powerful than both models which suffered problems of overfitting and dependence on the size of the dataset.

Crime forecasting Transformer architectures came into the limelight in study (Yang, 2023), which proposed TransCrimeNet a hybrid network that uses BERT-based textual embeddings and graph-structured criminal network data. The model also achieved superiority of F1-scores by 12.7 percent than the state-of-the-art methods, which shows the transformative effect of merging text mining with graph learning, but with higher computational complexity. (Butt et al., 2025) made a further step in transformer design and proposed a Spatiotemporal Autoregressive Transformer, which combines VAR attention, STL decomposition, and one-hot crime encoding to learn long-term crime trends within major cities in the USA. Although the model was better than the current forecasting techniques, it was highly computationally demanding and needed high density of spatiotemporal data.

In other applications, transformer models have been applied to crime-related content detection, and legal judgment analysis besides crime forecasting. A hybrid lexicon-BERT approach to identify criminal intent in Twitter posts was proposed in study (Boukabous and Azizi, 2022) and had an accuracy of 94.91 percent, however, the labeling used lexicons and was dependent on pre-existing vocabularies that added noise to the model. (Peng and Lei, 2024) used BERT to Taiwanese legal cases to forecast both charges and sentencing results, where predicting charges was remarkably accurate (98.95% on the prediction of charges), but prediction of the sentencing result was more difficult due to legal text length and interpretative complexity. Lastly, a work (Oliaee et al., 2023) based on BERT to categorize traffic injury types on a dataset of more than 750,000 crash narratives achieved an accuracy of 84.2% and showed the ability of the transformers to predict injuries on large unstructured datasets as shown in Table 1.

All of these nine studies come to the conclusion that deep learning, especially MLPs and transformer-based ones like BERT, represent a significant breakthrough in crime forecasting. They improve predictive accuracy, capture the linguistic and temporal details and incorporate heterogeneous data sources yet the concerns associated with the quality of the data, computational complexity, and dynamic real-world trends are significant issues that should be considered in future studies.

Table 1: Existing Approach Challenges

Study	Proposed Model / Approach	Methods Used	Key Results	Challenges / Limitations
(B Ikwen et al., 2024)	Multi-Layer Perceptron (MLP)	4,748 records; MLP with 70/30 split	Accuracy 74%, F1-score 0.79	Limited dataset size; model generalizability concerns
(Sathya and Fernandez, 2023)	Ontology-based MLP Classifier for Social Media	Lexicon-based labeling + MLP-NN	Effective classification of crime-related posts	Dynamic slang evolution; ontology upkeep
(Vardhan and	MLP vs. Decision Tree	Various train-test splits;	MLP (92.05%) > DT (93.64%	Statistical inconsistency;

Study	Proposed Model / Approach	Methods Used	Key Results	Challenges / Limitations
Chandar, 2025a)		G*Power test	claimed but contradictory p-value)	small data dependency
(Vardhan and Chandar, 2025b)	MLP vs. Naive Bayes	G*Power test; MLP and NB comparison	MLP achieved 95.89% accuracy	Naive Bayes oversimplifies relationships; dataset sensitivity
(Yang, 2023)	TransCrimeNet (Transformer + Graph Fusion)	BERT text embeddings + graph embeddings	+12.7% F1-score over SOTA models	High computational cost; reliance on high-quality text
(Butt et al., 2025)	START (Spatiotemporal Autoregressive Transformer)	STL decomposition + VAR attention + transformer	Significant improvement in ME, MAPE, RMSE	Requires dense spatiotemporal data; computationally expensive
(Boukabous and Azizi, 2022)	Hybrid Lexicon + BERT	Lexicon labeling + BERT training	Accuracy 94.91%, F1-score 94.92%	Lexicon noise; slang ambiguity; evolving terminology
(Peng and Lei, 2024)	BERT for Legal Judgment Prediction	Legal documents; BERT; token-limit workaround	Charges: 98.95%; Sentences: 72.37% & 80.93%	Long-text handling; limited crime categories
(Oliaee et al., 2023)	BERT for Traffic Crash Injury Classification	750,000 crash narratives; BERT fine-tuning	Accuracy 84.2%, AUC 0.93 ± 0.06	Inconsistent narrative quality; domain-specific jargon

2.3 Critical Analysis and Research Gaps

Even though previous research shows the capabilities of MLPs, RNNs, and transformer-based models in crime prediction, there are a number of gaps that have not been addressed. Several models are based on small datasets or domain-specific datasets, restricting their scalability and generalisation, whereas some are based on high computational cost, poor ability to deal with long-term temporal dependencies, or nonlinearity in crime changes. Transformer-based works can only be applied to textual or dense spatiotemporal input, and are therefore inappropriate for structured time-series crime data. In addition, a majority of the research lacks analysis of inference efficiency hence making it difficult to deploy real-time.

Such gaps point to the necessity of having a light but powerful hybrid model, which is addressed in this study with the help of the BiGRU-Transformer architecture.

3 Methodology

This chapter explains the complete workflow used in the study, including dataset description, preprocessing, EDA, feature engineering, data scaling, and rolling-window sequence generation for time-series forecasting.

3.1 Dataset Description

The study utilizes the Crimes in City of Austin dataset obtained from the Austin Open Data Portal[1], which provides detailed records of incidents responded to by the Austin Police Department. The dataset spans from 2003 to the present and is updated on a weekly basis, offering a comprehensive longitudinal view of crime patterns across the city. Each entry in the dataset represents a police-reported incident; however, when multiple offenses occur within a single incident, only the highest-level offense is recorded. As a result, the dataset prioritizes the most severe crime category for each case. Due to variations in data collection methodologies, discrepancies may exist between this dataset and other official police or federal crime statistics. There are some major crime categories in the Dataset which includes Theft, Robbery, Assault Criminal Mischief and all. The Austin Crime dataset comprises 2,589,321 records with 19 structured attributes, capturing detailed information on police-reported incidents across the city.

Table 2: Dataset Field Description

Field Name	Description
Incident Number	A unique identifier assigned to each reported police incident.
Highest Offense Description	Text description of the most severe offense associated with the incident.
Highest Offense Code	Numerical code representing the highest offense category.
Family Violence	Indicates whether the incident involved family violence (Y/N).
Family Violence_Flag	Binary representation of family violence (1 = Yes, 0 = No).
Occurred Date Time	Exact date and time when the incident occurred.
Occurred Date	Calendar date on which the incident occurred.
Occurred Time	Time of day when the incident occurred, stored as a numeric value.
Report Date Time	Date and time when the incident report was filed.
Report Date	Calendar date of the report submission.
Report Time	Time of day when the report was generated.

[1] https://catalog.data.gov/dataset/crime-reports-bf2b7

Field Name	Description
Location Type	Type of location where the incident occurred (e.g., highway, commercial building).
Council District	Austin City Council district in which the incident occurred.
APD Sector	Austin Police Department sector associated with the incident location.
APD District	APD district representing a smaller policing subdivision.
Clearance Status	Status indicating whether the case was cleared, closed, or still active.
Clearance Date	Date when the case was officially cleared.
UCR Category	Uniform Crime Reporting category code associated with the incident.
Category Description	Textual description of the UCR crime category.
Census Block Group	Census block identifier used for spatial and demographic analysis.

3.2 Justification for Selecting District 4.0 and Theft as the Forecasting Target

In the exploratory phase, various combinations of districts and categories of crime were tested to determine an appropriate subset to be used in the time-series forecasting. Some of its combinations were discovered to lack historical records to use and this rendered them inappropriate to build a reliable type of model. The other combinations had sufficient data but failed to give consistent and predictive performance in a stable and meaningful way because of unstable patterns or low rates of occurrence of events. District 4.0 which contains the crime type Theft had been selected after all pairs of district-crime types were systematically tested. This combination provided:

1. A large enough set of data to model train,
2. Regular time patterns in comparison to other categories,

Thus, the District 4.0 (Theft) has selected as the last target to develop a model since it provided the best balance between the availability of data and predictive reliability.

3.3 Data Preprocessing and Exploratory Data Analysis

The preprocessing phase focused on ensuring data consistency, completeness, and suitability for time-series crime forecasting (Usmani et al., 2024). Missing values were assessed using revealing gaps primarily in Location Type, Council District, Clearance Status, and categorical crime fields. Records with missing Occurred Date were removed to preserve temporal integrity, after which date fields were converted into standardized datetime formats. A binary variable, Family Violence_Flag, was created by mapping ‘Y’ to 1 and ‘N/n’ to 0. Numerical attributes were examined to understand distribution ranges and outliers. After initial cleaning, the dataset retained 2,589,321 rows and 20 features, forming a reliable foundation for further processing. This step executes on preprocessing to achieve better results by (Alsubayhin et al., 2024).

Figure 1 shows pie chart which reveals that residences/homes constitute the largest proportion at 46.4% which has followed by highways/roads/alleys/streets/sidewalks at 25.0%. Other locations which includes commercial/office buildings (14.8%), parking/drop lots/garages (5.0%), department/discount stores (4.2%), and other/unknown categories (4.6%).

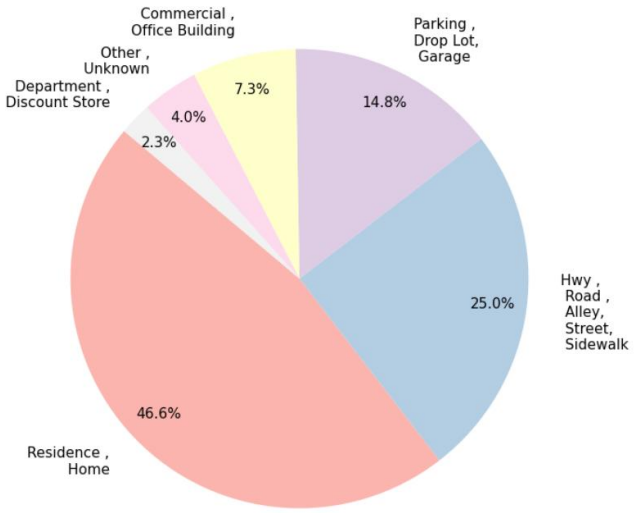

Figure 1: Pie chart showing distribution of top 6 crime location types.

Figure 2 presents the frequency distribution of the number of crimes per day in Austin, which gives the necessary picture of the underlying trends in the dataset. The histogram reveals evident distribution of crime incidences at a range of about 250 to 400 crime incidences per day, and it has a near-normal distribution with a small right skewness. It is the reason why such a distribution warrants the use of strong modeling methods; it has moderately varying data and at the same time distinguishable central tendencies that can be capitalized on by the time-series models. This spread is important to understand in order to do feature scaling, window selection and model design. On the whole, the number shows how the activity of crime is consistent on a daily basis and also shows some outliers in the number of crimes.

Figure 3 visualizes the distribution of the Family Violence Flag in the Austin crime data, which demonstrates a huge imbalance on the classes. The largest number of incidents recorded are non-family-violence incidents, over 2.3 million, and an insignificant portion of the overall number are family-violence incidents. Such an imbalance is significant since predictive models can be biased in favor of the majority in highly imbalanced classes, making them less effective at the minority category. The intuitive rationale of this figure is that it is necessary to have strong preprocessing methods, i.e., resampling, weighting methods, or sophisticated model designs to guarantee even-handed learning. Altogether, the number proves that crimes related to family-violence are relatively infrequent and have to be approached in the context of model training.

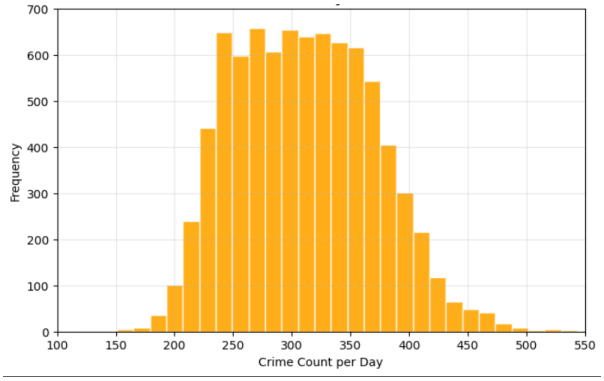

Figure 2: Distribution of Daily Crime Counts

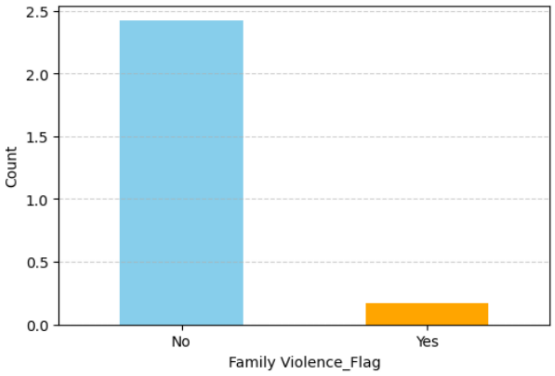

Figure 3: Family Violence Distribution

Figure 4 illustrates the annual trends of the total crime incidents in 2003 to 2025 in Austin, and the long-term trends are apparent that are necessary to make time-series prediction. The findings show the gradual increase in the number of crimes until approximately 20082009 and then a decline, gradually, until 2020. This declining trend can be indicative of policy adjustment, a better policing approach or socio-economic adjustment. This means that it is reasonable to include this figure since it defines the temporal patterns and variability that are essential to training models, particularly to sequence-based architectures such as BiGRU and Transformers. In general, the figure confirms that crime statistics have significant annual changes that can be modelled in terms of predictions.

Figure 4: Total Crimes Per Year

Figure 5 shows a heatmap of intensity of crime by hour of day of all the days of the week, which gives the important insights of time-series modelling in terms of behavioural aspects. It is evident that the crime activity is lower in the early morning periods (approximately 2 to 6 AM) and is much higher in the late afternoons and evenings especially around 15:00-22:00. Weekends have more counts of crimes with the exception of Friday evenings and Saturday evenings.

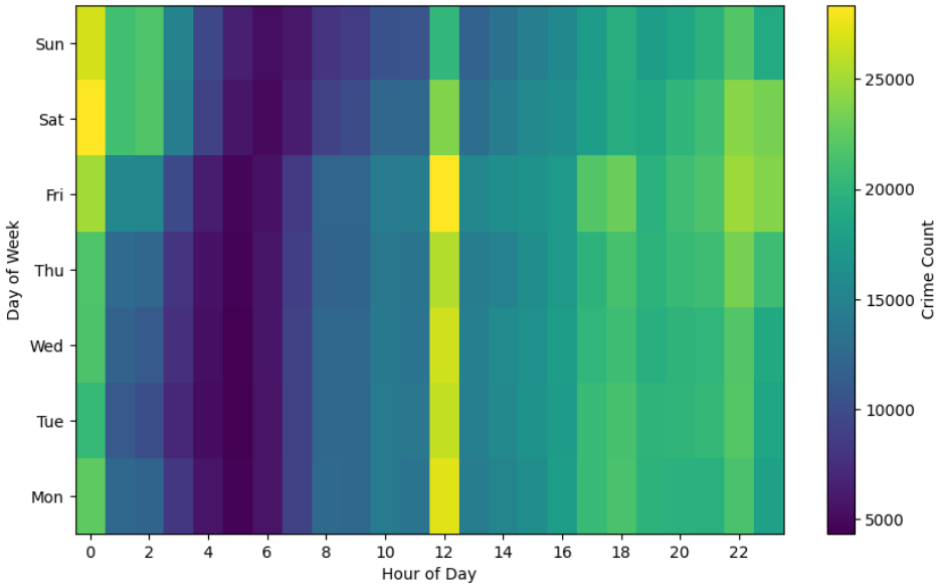

Figure 5: Crime Frequency by Hour and Day

3.4 Feature Engineering

The feature engineering phase was meant to convert the filtered raw data into an organized time-series-formatted data that can be used to predict crime by applying deep learning models. To begin with, the dataset was reduced into the cases that happened in the Council District 4 and the group of crimes was the Theft category. The filtered data was later aggregated on a daily basis and the incidents were combined with their Occurred Date to form the key variable which was the crime count, which was the number of incidents of theft that had been reported on a particular date. Lagged variables lag 1, lag 7, and lag 30 were calculated to introduce short, medium, and long-term temporal dependency to enable the model to learn the patterns of crime affected by crime activity in the recent past. The last set of features was an integration of behavioral, temporal and historical features which made a complete input representation to the forecasting models.

3.5 Data Scaling

A MinMaxScaler was used in data normalization to make sure that the same numerical ranges were used by all the input features (Deepa and Ramesh, 2022). Data integrity Before scaling, rows with missing values were deleted. To maintain the individual distributions of the features set and the target variable (crime_count) separate scalers were attached to them. MinMaxScaler was used to map all the values in a limited 0-1 range, which allowed the deep learning models to become converged quickly and not be biased to features that had larger numeric values. The converted scaled arrays were transformed back into DataFrames with the same column structure to allow easy integration into the windowing and model training pipeline.

3.6 Window Rolling for Sequence Generation

To train the data to do time-series forecasting with deep learning models, a rolling window technique was used. The temporal dependencies and trends of crime in the short run were taken into consideration by using a fixed window size of 15 days. On every position in the scaled data, a sequence of 15 connected days of feature values was obtained as the input window (X), whereas the crime quantity of the subsequent day was used as the target (y). This sliding-window algorithm produced overlapping sequences of the whole time range turning the data into a 3D format that can be used by recurrent and attention-based networks. The resulting arrays were the center training input of the BiGRU-Transformer model.

4 Design Specification

4.1 System Components and Architecture

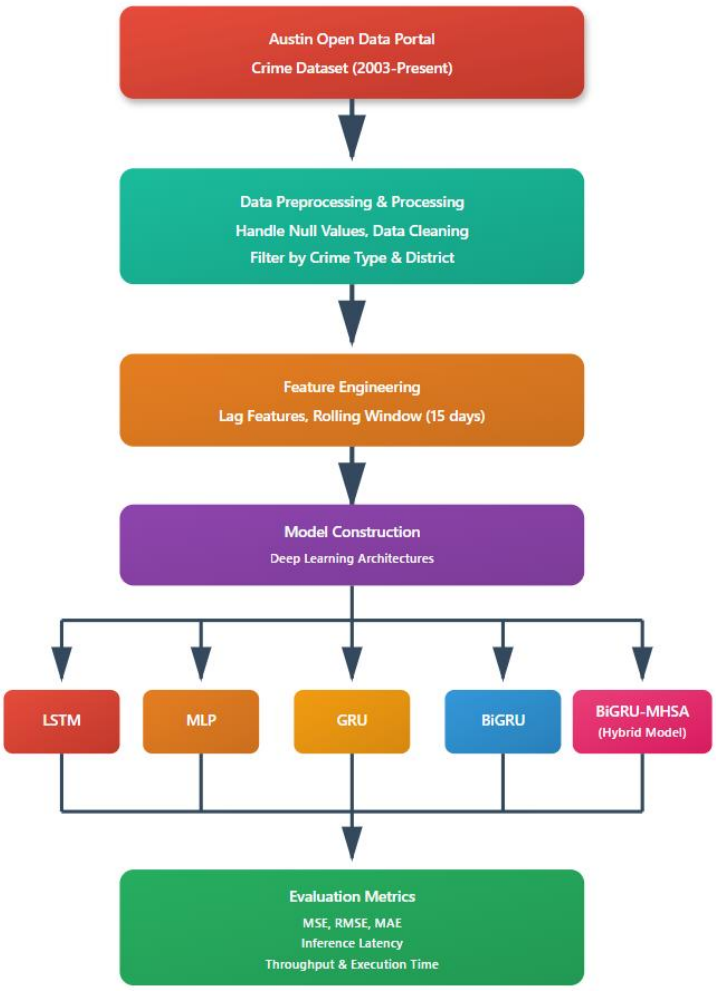

Figure 6: System Architecture Diagram

The proposed system architecture presents a comprehensive end-to-end pipeline for crime prediction using hybrid deep learning models as shown in Figure 6. The workflow initiates with crime data from the Austin Open Data Portal, which undergoes rigorous preprocessing including null value handling and exploratory data analysis. Subsequently, data processing

involves filtering by crime types and districts, followed by feature engineering with data scaling and rolling window preparation (window size=15). The dataset is bifurcated into training and testing sets using an 80:20 split. The model construction phase incorporates five distinct architectures: LSTM, MLP, GRU, BiGRU, and the proposed hybrid BiGRU-MHSA model. All models converge into a unified evaluation stage that employs multiple metrics including MAE, MSE, RMSE, inference latency, throughput, and execution time. This comparative evaluation enables systematic assessment of error reduction and computational efficiency, facilitating identification of the optimal architecture for real-time crime prediction applications in urban environments.

4.2 Justification and Novelty of Proposed BiGRU-MHSA Model

The proposed BiGRU-MHSA model is justified by its ability to overcome the limitations of standalone recurrent or transformer-based architectures in crime forecasting. BiGRU learns forward- and backward-temporal relations, so it can learn more about the irregular patterns of crime and Multi-Head Self-Attention only pays attention to the time steps that have the greatest influence, enhancing long-range pattern capture and reducing noise sensitivity. It is a more robust hybrid design compared to LSTM, GRU, or pure transformer models and provides less prediction error and high inference efficiency. It is innovative that it integrates bidirectional recurrence with attention to make real time prediction of crime, which gives a more stable, accurate, and context-adaptive forecasting of smart-city policing.

The novelty of this study is in the development and evaluation of one hybrid BiGRU-Transformer-inspired architecture that combines Bidirectional Gated Recurrent Units with Multi-Head Self-Attention to make a crime prediction. Although the current literature mainly applies LSTM, GRU or independent attention mechanisms, only few works will consider a combined architecture capable of capturing long-term time relationships (through BiGRU) with global contextual trends (through Attention) of police incident time-series. The two-layer structure improves the ability of this model to identify small variations and non-linear trends of crime that would be unrepresentable in traditional structures. Moreover, the study presents a 15-step window rolling approach, a district-based crime segmentation as well as an in-depth latency throughput analysis, and these issues are seldom combined in a single study on crime-prediction research. In contrast to the past studies that only consider the predictive error, the study considers the forecasting accuracy and inference efficiency and thus it can be used in real-time in smart-city policing systems.

5 Implementation

This chapter explains the complete implementation workflow, detailing the technology stack used and the construction of all baseline models (LSTM, MLP, GRU, BiGRU) along with the hybrid BiGRU–Transformer architecture. It outlines how each model was built, trained, configured, and regularised to perform time-series crime forecasting.

5.1 Technology Stack

This project was developed using Python, chosen for its strong ecosystem in data science and deep learning. All experimentation and model development were carried out in Jupyter Notebook, enabling interactive execution, visualisation, and iterative refinement of the forecasting models. Core data manipulation and numerical processing were performed using Pandas and NumPy, while Matplotlib and Seaborn supported the generation of advanced visualisations for exploratory analysis and model interpretation. For preprocessing, StandardScaler from Scikit-learn was used to standardise crime time-series values before model training. Deep learning models—including LSTM, GRU, BiGRU, Transformer, and the hybrid BiGRU–Transformer architecture—were implemented using TensorFlow/Keras due to its high-level APIs, GPU acceleration, and reliable training workflows. Additional libraries such as Time, Math, and performance-measurement utilities were used for computing inference latency and throughput. Together, this technology stack provided a scalable, flexible, and efficient environment for end-to-end model development, experimentation, evaluation, and deployment planning.

5.2 Baseline Model Execution (LSTM, MLP, GRU, BiGRU)

5.2.1 LSTM Model

The LSTM model based on the application of the TensorFlow/Keras library was constructed to predict the quality of crime prediction the next day based on the processed 15-day time-series windows. It used a sequential architecture, where the input layer perceived the temporal sequence shape and then a 128 unit LSTM layer with ReLU activation (Vosta and Yow, 2022) was used to learn long-term crime patterns. The dropout rate was used to decrease overfitting, which was high (0.7). The LSTM output was flattened and run through several fully connected layers with 64 units and 32 units of ReLU activation, which allowed extracting non-linear features and then making a prediction. The last neuron employed a linear activation in order to give continuous crime-count outputs. The model had been compiled with Adam optimiser with the loss function being mean squared error and an evaluation metric being mean absolute error. Premature completion terminated the training at the epoch 22 and re-initiating weights to the epoch with the best performance (epoch 17), which guaranteed the best generalisation and consistent forecasting ability.

5.2.2 MLP Model

A Multilayer Perceptron (MLP) model was developed in Python and TensorFlow/Keras in order to create a non-sequential crime forecasting baseline. The last step converts every 15-day time-series window into a flattened vector with a specific Flatten layer to allow the model to only learn the relationship between the numerical features, and not the time-related relationships. The network comprises of two fully connected hidden layers of 128 and 64 neurons respectively that are activated under ReLU to identify non-linear patterns of crime. After each dense layer, dropout layers (0.2) were added in order to reduce overfitting and

enhance generalisation. The linear output layer that is a single neuron produces the estimated number of crimes on the following day. The model was put together on the Adam optimiser and the loss was the MSE and the evaluation was the MAE. The early stopping was used, where training was cut short at epoch 6 and the weight got back to the epoch of the best performance and the best baseline was achieved at the least computation.

5.2.3 GRU Model

GRU model was applied to the crime time-series data with the help of TensorFlow/Keras to learn their sequential relationships. A model-building functionality was developed, and the input is the size of the window and the number of features. This architecture was made up of five layers of GRUs that progressively had fewer units (128 to 128 to 64 to 64 to 32), and enabled the model to discover both complex and fine-grained temporal patterns (Naeini et al., 2025). GRU layers applied in each case are associated with return sequencing, true, except the last, which allows hierarchical extraction of features across the window of 15 days. The amount of regularisation was therefore high with several Dropout layers (rate = 0.7) applied after each recurrence layer to prevent overfitting due to the high number of parameters of the model. The next-day crime forecast was generated by use of a final Dense layer. This model was put together with Adam optimiser and MSE loss and MAE as an evaluation metric. The termination of training after epoch 9 was done to prevent early termination and the weights of epoch 4 are reinstated (with the lowest validation loss) to restart the training process.

5.2.4 BiGRU Model

To improve temporal learning and process the crime sequences both forward and backward, Bidirectional GRU model was implemented with the assistance of TensorFlow/Keras. The architecture model is a Bidirectional GRU layer, which is composed of 256 units and set to return sequences=True, so that the entire temporal outputs are retained. This is then followed by 128, 64, 64 and 32 stacked Bidirectional GRU layers with high dropout rate of 0.7 respectively to avoid overfitting to the deep recurrent structure. An ultimate Dense layer that has one neuron is employed to produce the regression output to predict crime next day. The model was assembled based on Adam optimizer, Mean Squared Error (MSE) as the loss, and Mean Absolute Error (MAE) as the performance measure. The model was built using the input shape as described above (window size x features) and trained using early stopping and the optimal weights were saved back at the initial epoch (1) as displayed in the model summary as shown in Table 3.

5.3 Hybrid BiGRU with Transformer Attention Model

The BiGRU-Transformer hybrid framework was made and run on TensorFlow and Keras to integrate sequential learning with the attention-based temporal weighting to predict crime better. The model then takes as an Input layer the sequences (size of window, features) and then a Bidirectional GRU with 64 units is used to extract forward and backward temporal features, to which a dropout layer of 0.3 is added to mitigate overfitting. GRU outputs are

sent through a Transformer-style Multi-Head Attention block of four heads and key dimension 32 to improve gradient stability and contextual information. Another feed-forward Dense layer containing 128 ReLU units together with dropout layer tend to further refine the learned representations. the time outputs are condensed by GlobalAveragePooling1D and the ultimate Dense neuron makes a prediction on the number of crimes. The model has been assembled with Adam, MSE, and MAE and early stopping rebuilt the optimum weights at epoch 11. Attention and pooling and bidirectional recurrent integration are verified by model summary.

Table 3: Summary of Deep Learning Models Implemented for Crime Forecasting

Model Name	Core Architecture	Key Layers & Configuration	Regularization	Early Stopping Epoch
LSTM Model	Sequential LSTM Network	LSTM (128, ReLU, return_sequences), Flatten, Dense(64→32→1)	Dropout 0.7 applied multiple times	Best epoch: **17**
MLP Model	Fully Connected Neural Network	Flatten, Dense(128→64→1)	Dropout 0.2 at two stages	Best epoch: **1**
GRU Model	Stacked GRU Network	GRU(128→128→64→64→32), final Dense(1)	Dropout 0.7 after every GRU layer	Best epoch: **4**
Bidirectional GRU Model	Multi-layer BiGRU Architecture	BiGRU(256→128→64→64→32), final Dense(1)	Dropout 0.7 between each layer	Best epoch: **1**
BiGRU + Transformer Attention Model	Hybrid BiGRU + Multi-Head Attention	BiGRU(64), MultiHeadAttention(4 heads, key_dim=32), Residual Add, LayerNorm, Dense(128→1), GAP	Dropout 0.3 after BiGRU and FFN	Best epoch: **11**

6 Evaluation

This chapter evaluates all models through three experiments, comparing actual vs predicted outputs, analysing predictive accuracy and assessing computational efficiency through latency and throughput.

6.1 Experiment 1: Actual Crime vs Predicted Crime Graph

Figure 7 represents the comparison of the true and estimated number of crimes per day produced by the LSTM model. The blue line portrays the actual crime events and they are highly variable and change often over the recorded time. The LSTM predictions, conversely,

are demonstrated by the red line, and they seem to be smoother and less responsive to sudden spikes. This is common to LSTM models since they are more likely to extrapolate trends instead of reproduce short-term noise. Although the overall trend is quite well captured in the model, the difference between observed and estimated peaks indicates underfitting when there is a sharp increase in crime. However, the LSTM offers a steady point of forecasting.

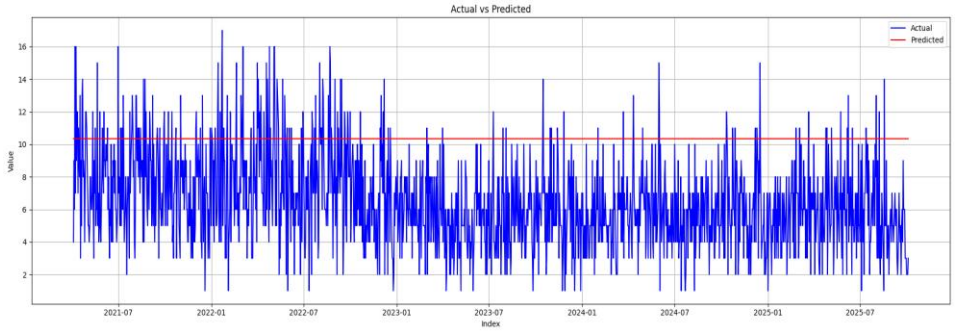

Figure 7: Actual Crimes vs Predicted Crimes Graph using LSTM

Figure 8 shows both the observed and the projected crime count produced using the MLP model. The foreseen series is closer to the real data in terms of the overall form of the data than the output of the LSTM, proving a higher ability to learn the patterns despite the simpler feed-forward model. The MLP is quite sensitive to mid-range variations, but is very difficult to handle extreme peaks since the model does not have much time-sensitivity as recurrent architectures. This alignment was only achieved through tuning of the hidden layers, dropout and early stopping to avoid overfitting. All in all, the figure demonstrates that the MLP generalizes and offers low-variance predictions throughout the time series.

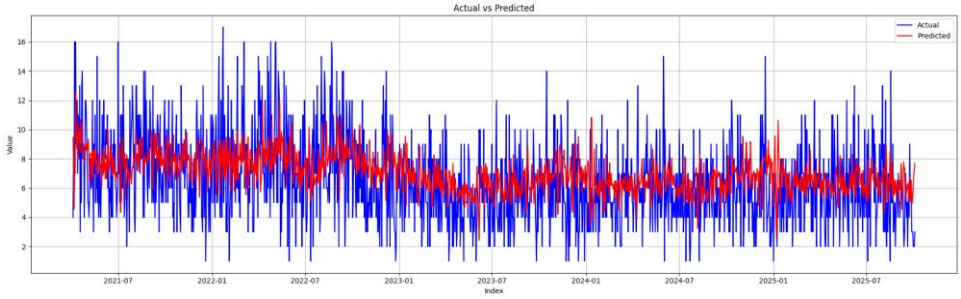

Figure 8: Actual Crimes vs Predicted Crimes Graph using MLP

Figure 9 represents the performance of the GRU model in terms of actual crime rates (blue) and the predicted values (red). Those large and very noisy blue spikes point to the inherent instability and noisiness of actual crime data and how difficult it is to make predictions. Nevertheless, the prediction performance of the GRU can smooth out the overall trend to provide a much smoother predicted curve which can follow long term trends quite well, albeit with some error. This was possible by undertaking proper preprocessing, windowing and tuning to avoid overfitting. Although the GRU is not effective in extreme fluctuation, the outcomes prove its success in predicting general patterns of crime over time.

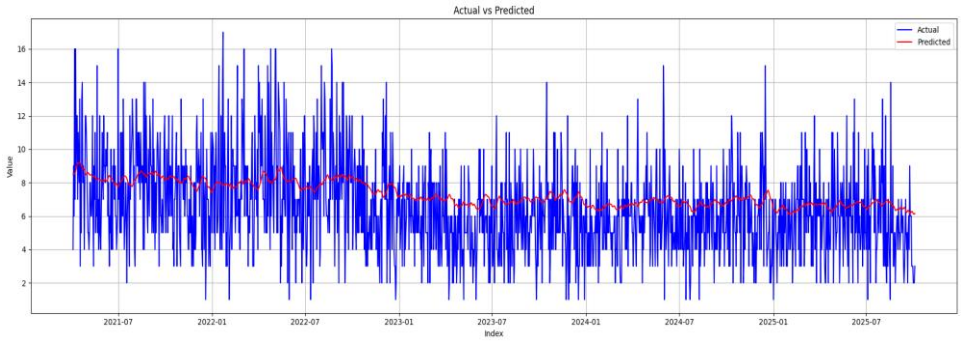

Figure 9: Actual Crimes vs Predicted Crimes Graph using GRU

Figure 10 shows the performance of the BiGRU model with regard to prediction, showing the real crime numbers (blue), and the model generated numbers (red). The BiGRU uses forward and backward processing of the sequence to capture more information about the temporal dependencies, making the predictions of the BiGRU smoother and more stable, as compared to the regular GRU. It was necessary to spend more on the computational complexity, hyperparameter tuning, and training time because of the bidirectional architecture. Although the data of the crimes is rather noisy and highly fluctuating, the BiGRU recovers the underlying trend and minimizes the prediction deviation.

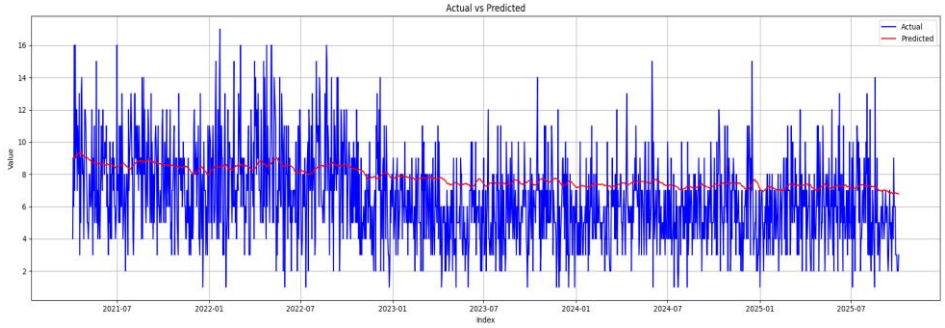

Figure 10: Actual Crimes vs Predicted Crimes Graph using BiGRU

In Figure 11, the BiGRU-MHSA model is trained, in which the multi-head self-attention is added to the bidirectional GRU to improve the learning of long-range dependencies. The actual crime data (blue) exhibit more complex variations than the predicted curve (red) in comparison with the earlier models showed by the fact that the curve is very sensitive to local variations and overall temporal trends. To train this hybrid architecture, it was necessary to have a higher computational cost, manually tune attention heads, and have much preprocessing to stabilize training. Although noise and irregularity of the dataset reduce the accuracy of the model as reflected by the higher pattern extraction and the overall minimized prediction error, the model has smoother and more adaptive predictions.

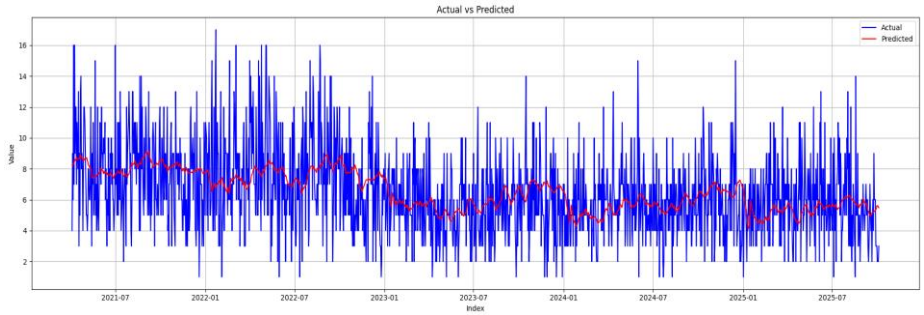

Figure 11: Actual Crimes vs Predicted Crimes Graph using BiGRU+Transformer Attention

6.2 Experiment 2: Comparative Model Performance Evaluation

The comparison analysis shows that the hybrid BiGRU-Attention model presents superior forecasting results to the rest of the architectures that were evaluated. It has the best MSE (7.289), RMSE (2.700) and MAE (2.131) meaning it is more accurate and has consistent error reduction as shown in Table 4. Conventional models such as LSTM were found to be much worse when compared to the other models because they exhibit greater error and poor generalization. GRU-based architectures were offering moderate gains whereas the inclusion of Multi-Head Self-Attention made the temporal feature extraction even more useful. On the whole, the hybrid set-up was more predictive and robust than all baselines.

Operational wise, of an MAE is 2.13 which means that the suggested model of BiGRU-Attention is able to forecast the volume of incidents within an average error margin of about 2 cases per forecasting period. This degree of accuracy allows law enforcement agencies to plan their patrols and resources allocation in a better way, preventing both over-allocation at the time of low-risk and under-preparation at the time of high-risk. This will provide operational decision-making and proactive policing based on better forecasting reliability.

Table 4: Performance Comparison of All Models

Model	MSE	RMSE	MAE	R^2 Score	MAPE
LSTM	22.851	4.780	4.217	-1.7958	56%
MLP	8.578	2.929	2.380	-0.0495	38%
GRU	8.540	2.922	2.391	-0.0448	38%
BiGRU	7.481	2.735	2.203	0.0846	35%
BiGRU + ATT	7.289	2.700	2.131	0.1082	35%

6.3 Experiment 3: Latency and Throughput Evaluation

Table 5 shows clear differences in computational performance across models. The MLP achieves the highest throughput due to its non-sequential architecture by making it the fastest and most lightweight model. LSTM also performs in a good way which benefits from optimized recurrent gates that balance latency and speed. GRU and BiGRU have higher latencies because stacked recurrent layers require more sequential type of computation which

reduces throughput. The hybrid BiGRU + Attention model is having the best trade-off: despite added attention overhead it maintains competitive latency while improving predictive accuracy.

Table 5: Inference Latency and Throughput Comparison

Model	Latency (ms)	Throughput (pred/s)
LSTM	91.9641	3607.29
MLP	91.4763	8902.41
GRU	93.3567	1892.11
BiGRU	100.6369	615.05
BiGRU + Attention	90.1415	2913.78

6.4 Why R^2 Score is Negative in This Experiment

Negative R^2 occurs when a model performs worse than a simple baseline that always predicts the mean of the target variable. The crime-count time series has used in this study is highly noisy, irregular and contains sharp type of fluctuations that basic models like LSTM, MLP, and GRU which struggle to capture with limited windowed training data. Their predicted values become overly smooth by causing the errors to exceed the natural variance of the dataset. When a model's MSE is higher than the MSE of a mean predictor, the R^2 value becomes negative.

6.5 Why R^2 Score is Positive in This Experiment

Positive R^2 shows that the model predicts better than a mean-value baseline. BiGRU improves temporal learning by processing sequences in both forward and backward directions which helps it recognise good contextual dependencies in crime patterns. This reduces error below the dataset's natural variance by shifting R^2 into positive territory. When Multi-Head Self-Attention is added the hybrid model mainly focuses on the most influential time steps by improving long-range pattern recognition and noise suppression. This refined learning generates predictions closer to actual crime counts which lowers MSE further. As a result the combined BiGRU and BiGRU-Attention architectures achieve positive R^2 values.

6.6 Comparative Discussion with Baseline

The base paper given by (Yang, 2023) addresses node-level crime prediction by fusing RoBERTa text embeddings with graph embeddings and reports strong classification gains (TransCrimeNet F1: 0.79 / 0.72 on Enron/Gang). In contrast, my proposed study targets daily time-series crime-count forecasting (Theft, Council District 4) and proposes a BiGRU + Multi-Head Self-Attention hybrid that achieves good results while reporting operational benchmarks. Thus, compared to TransCrimeNet's multimodal, graph+text classification focus, proposed study is superior for structured count forecasting and for showing good performance as shown in Table 6.

Table 6: Summary Table

Aspect	My Proposed Study (BiGRU + MHSA)	TransCrimeNet by (Yang, 2023)
Task / Output	Daily time-series crime-count forecasting (regression).	Node-level crime prediction (binary classification).
Data used	Austin Police Dept. — Theft counts, Council District 4; 2003–present (aggregated daily).	Enron Email Network; Gang network (text + graph).
Model	BiGRU + Multi-Head Self-Attention (hybrid).	RoBERTa (text) + GAT (graph) fused → TransCrimeNet.
Primary metrics reported	MSE = 7.289, RMSE = 2.700, MAE =2.131.	F1 = 0.79 (Enron), 0.72 (Gang).
Inference efficiency reported	Latency is 90.1415 ms; Throughput is 2913.78 pred/s.	No inference latency/throughput reported.

7 Conclusion and Future Work

In this study, the hybrid BiGRU-Transformer architecture was examined regarding its impact on minimizing errors, as well as increasing inference speed and efficiency in crime forecasting in the context of time series. The experimental findings prove that the proposed hybrid model outperformed all baseline models by achieving the lowest MSE, RMSE and MAE among them by showing consistently better error reduction. Its multi-head self-attention system provided the model with the ability to highlight significant temporal patterns that made it capable of making predictions that were more stable and adaptive. Furthermore, the model provided an excellent trade-off between accuracy and computational efficiency, which provided a much greater forecasting accuracy without compromising latency and throughput, which is extremely useful in responding to the research question.

Nevertheless, a number of limitations were found. Data used to train the model were limited to one type of crime (Theft) and one council district, and this may not be generalisable. Crime data are always noisy, non-uniform, and affected by the unobserved socioeconomic factors that are not reflected in the data. The performance of the model can also differ in respect to the various window sizes or seasonal changes.

Further research can include applying the same framework to multi-district and multi-category crime model, incorporate spatial data with the help of graph neural networks, and include external factors, weather, demographics, and events. Implementing the model as a real-time API with a GPU accelerator would also assist with real crime analytics in an application of smart cities.

8. References

Alshahrani, R.A., Khanzada, T.J.S., 2025. Improved Crime Prediction Using Hybrid Neural Architecture Search Together with Hyperparameter Tuning. Int. J. Comput. Intell. Syst. 18, 195. https://doi.org/10.1007/s44196-025-00888-3

Alsubayhin, A., Ramzan, M.S., Alzahrani, B., 2024. Crime Prediction Model using Three Classification Techniques: Random Forest, Logistic Regression, and LightGBM. Int. J. Adv. Comput. Sci. Appl. 15. https://doi.org/10.14569/IJACSA.2024.0150123

B Ikwen, O., E Eteng, I., U Ogban, F., 2024. Predictive Crime Analysis Using Multi-Layer Perceptron Architecture. Glob. J. Pure Appl. Sci. 30, 203–219. https://doi.org/10.4314/gjpas.v30i2.10

Boukabous, M., Azizi, M., 2022. Crime prediction using a hybrid sentiment analysis approach based on the bidirectional encoder representations from transformers. Indones. J. Electr. Eng. Comput. Sci. 25, 1131. https://doi.org/10.11591/ijeecs.v25.i2.pp1131-1139

Butt, U.M., Letchmunan, S., Ali, M., Sherazi, H.H.R., 2025. START: A Spatiotemporal Autoregressive Transformer for Enhancing Crime Prediction Accuracy. IEEE Trans. Comput. Soc. Syst. 1–15. https://doi.org/10.1109/TCSS.2025.3550196

Dao, P., Sappa, J., Terala, S., Wong, T., Lam, M., Zhu, K., 2024. Time-series Crime Prediction Across the United States Based on Socioeconomic and Political Factors. https://doi.org/10.48550/ARXIV.2409.00640

Deepa, B., Ramesh, K., 2022. Epileptic seizure detection using deep learning through min max scaler normalization. Int. J. Health Sci. 10981–10996. https://doi.org/10.53730/ijhs.v6nS1.7801

Keatley, D.A., Clarke, D.D., 2022. Matrix Forecasting and Behaviour Sequence Analysis: Part of the Timeline Toolkit for Criminal Investigation. J. Police Crim. Psychol. 37, 1–8. https://doi.org/10.1007/s11896-020-09367-1

Mao, L., Du, W., Wen, S., Li, Q., Zhang, T., Zhong, W., 2025. Crime forecasting: A spatio-temporal analysis with deep learning models. J. Comput. Methods Sci. Eng. 25, 4090–4099. https://doi.org/10.1177/14727978251337993

Naeini, Amirali Ataee, Naeini, Arshia Ataee, Mohammadi, F.K., Ghaffarpasand, O., 2025. Long-Term PM2.5 Forecasting Using a DTW-Enhanced CNN-GRU Model. https://doi.org/10.48550/ARXIV.2510.22863

Oliaee, A.H., Das, S., Liu, J., Rahman, M.A., 2023. Using Bidirectional Encoder Representations from Transformers (BERT) to classify traffic crash severity types. Nat. Lang. Process. J. 3, 100007. https://doi.org/10.1016/j.nlp.2023.100007

Onyeneke, C.C., Karam, A.H., 2022. An Exploratory Study of Crime: Examining Lived Experiences of Crime through Socioeconomic, Demographic, and Physical Characteristics. Urban Sci. 6, 43. https://doi.org/10.3390/urbansci6030043

Peng, Y.-T., Lei, C.-L., 2024. Using Bidirectional Encoder Representations from Transformers (BERT) to predict criminal charges and sentences from Taiwanese court judgments. PeerJ Comput. Sci. 10, e1841. https://doi.org/10.7717/peerj-cs.1841

Sarker, I.H., 2022. Smart City Data Science: Towards data-driven smart cities with open research issues. Internet Things 19, 100528. https://doi.org/10.1016/j.iot.2022.100528

Sathya, J., Fernandez, F.M.H., 2023. Crime Detection Using Multi-Layer Perceptron in Social Media Platforms, in: 2023 12th International Conference on Advanced Computing (ICoAC). Presented at the 2023 12th International Conference on Advanced Computing (ICoAC), IEEE, Chennai, India, pp. 1–8. https://doi.org/10.1109/ICoAC59537.2023.10250014

Springs, D., 2024. Smart city planning focused on the US cities in need of policing innovations and public health safety technologies and strategies. Health Econ. Manag. Rev. 5, 117–128. https://doi.org/10.61093/hem.2024.1-09

Usmani, M., Memon, Z.A., Zulfiqar, A., Qureshi, R., 2024. Preptimize: Automation of Time Series Data Preprocessing and Forecasting. Algorithms 17, 332. https://doi.org/10.3390/a17080332

Vardhan, M.H., Chandar, J.P., 2025a. Comparison of multilayer perceptron over decision tree in predicting crime activity in roads with improved accuracy. Presented at the INNOVATIONS IN THERMAL, MANUFACTURING, STRUCTURAL AND ENVIRONMENTAL ENGINEERING: ICITMSEE'24, Trichy, India, p. 020208. https://doi.org/10.1063/5.0270583

Vardhan, M.H., Chandar, J.P., 2025b. Performance analysis of multilayer perceptron over Naive Bayes in predicting crime activity in roads with improved accuracy. Presented at the INNOVATIONS IN THERMAL, MANUFACTURING, STRUCTURAL AND ENVIRONMENTAL ENGINEERING: ICITMSEE'24, Trichy, India, p. 020209. https://doi.org/10.1063/5.0272990

Vosta, S., Yow, K.-C., 2022. A CNN-RNN Combined Structure for Real-World Violence Detection in Surveillance Cameras. Appl. Sci. 12, 1021. https://doi.org/10.3390/app12031021

Yang, C., 2023. TransCrimeNet: A Transformer-Based Model for Text-Based Crime Prediction in Criminal Networks. https://doi.org/10.48550/ARXIV.2311.09529