GCN-GRU: A Spatiotemporal Deep Learning Framework Integrating Graph Convolution and Gated Recurrent Networks for Crime Prediction

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Abstract: Law enforcement agencies rely on accurate crime prediction systems to study past and present crime trends in order to forecast and prevent future incidents. Among Deep Learning (DL) approaches, time series prediction using Long Short-Term Memory (LSTM) networks is popular because modeling long-term temporal dependencies and sequential patterns is necessary for crime data. However, LSTM struggles with large number of parameters due to three gates, difficulty in capturing very short-term dependencies and increased memory consumption, limits the prediction on real-time crime datasets. For spatial learning, Graph Convolutional Networks (GCNs) have been used to capture crime area based correlations and spatial dependencies in crime data. However, GCN often overfit to local graph structures, struggle to extract transferable features across diverse regions and exhibit reduced performance when spatial data is noisy or incomplete. To overcome such limitations a Graph Convolutional Network with Gated Recurrent Unit (GCN-GRU) is put forward in this paper to enhance crime prediction. In this model, GCN dynamically adapts the graph topology based on spatial data characteristics to extract relevant features across diverse spatial regions in the crime dataset. Also, this mechanism captures both local and global spatial dependencies improve resilient to noisy or incomplete data. By updating neighborhood relationships during training, GCN avoids dependence on fixed local structures reducing overfitting and improving spatial feature stability. GRU employs only two gates (reset and update) with fewer parameters enabling faster training and lower memory usage. Moreover, the reset gate enhances the handling of sudden and short-term variations in sequential crime data while preserving the ability to technique long-standing needs. In the temporal modeling module, GRU network captures the underlying relationships between sequential crime events and their temporal patterns. Along with this Cross-Entropy Loss function is employed to help the method to give greater probabilities to correct crime categories to improve classification accuracy and enhance decision confidence in crime prediction. Thus, GCN improves spatial feature mapping and GRU enhances temporal sequence learning in enhanced crime classification. Experimental results demonstrate that the proposed GCN-GRU outperforms existing baseline approaches in crime prediction.

Keywords: *Crime Prediction, DL, LSTM, Cross Entropy Loss Function and Spatial Temporal Feature.*

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I. INTRODUCTION

The ability for law enforcement to proactively forecast and prevent future criminal acts through the analysis of both historical records and real-time incident reports makes crime prediction an essential component of contemporary urban safety management [1]. By detecting patterns and correlations in crime data, authorities can optimize resource allocation, improve patrol scheduling, and enhance strategic decision-making to ensure public safety. However, the dynamic nature of crime poses significant challenges, as criminal activities are influenced by multiple factors such as location, time, social dynamics, and environmental conditions, which make the prediction problem both spatially and temporally complex [2].

LSTM networks are popular in temporal modeling because to their ability to detect patterns and dependencies in sequential data that persist over time [3,4]. This is useful for crime datasets, which often exhibit seasonal variations alongside sudden, irregular events. However, LSTMs require

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training a large number of parameters due to their three-gate structure (input, forget, output) [5], leading to high computation, long training times, and memory overheads. They may also struggle to adapt to abrupt short-term changes in crime patterns [6].

For spatial modeling, GCNs have shown promise by representing crime-prone areas as graph nodes and using edges to model spatial relationships [7,8]. This allows GCNs to aggregate context from neighboring regions. However, traditional GCNs can overfit to local structures, struggle with varying spatial patterns, and perform poorly when data is noisy or incomplete due to their fixed graph topology [9,10].

To solve this issue, this paper proposes an GCN-GRU for improved crime prediction. In this model, GCN dynamically adapts the graph topology based on spatial data characteristics to extract relevant features across diverse spatial regions in the crime dataset. This method improves resilience in the face of incomplete or noisy data by successfully capturing both global and local spatial dependencies. By updating neighborhood relationships during training, GCN reduces reliance on fixed local structures, thereby minimizing overfitting and improving the stability of spatial feature representations. The GRU component employs only two gates are reset and update, which reduces the number of parameters, enabling faster training and lower memory usage compared to LSTM. The reset gate strengthens the technique's facility to handle sudden and short-term variations in sequential crime data, while still preserving the capacity to model long-term dependencies.

In the sequence learning module, GRU captures the underlying relationships between sequential crime events and their temporal patterns. Applying the Cross-Entropy Loss function further improves classification accuracy by training the network to provide more weight to the right types of crimes, which boosts prediction accuracy and decision confidence. Thus, GCN enhances spatial feature mapping, while GRU improves temporal sequence learning for more effective crime classification. Experimental evaluations show that GCN-GRU achieves superior accuracy, resilience to data noise, and faster computation compared to baseline models, confirming its effectiveness for real-time crime prediction tasks.

The remaining sections of this study are designed as follows: Section II summarizes the related literature. Section III describes the GCN-GRU model. Section IV presents the experimental outcomes and Section V concludes the work together with discussing possible future improvements.

II. LITERATURE SURVEY

Liang et al. [11] proposed a Neural Attentive framework for Hour-level Crime prediction (NAHC) to enhance crime forecasting performance in fine grained temporal settings. To address the negative-inflated issue, a knowledge-based data improvement technique was used in advance. Using multi-graph convolution, we built three distinct kinds of graphs to represent spatial dependency from all directions. To describe temporal dependency and capture external influences, gated recurrent units combined with a temporal attention mechanism were used. A fully connected network was used to get the final prediction results after learning representations using a categorical attention mechanism that was developed to handle categorical dependency. On the other hand, dealing with extremely sparse data with little contextual information may impact the model's performance.

Dong et al. [12] created a deep Spatio-Temporal 3D convolutional neural network (ST3DNetCrime), for the purpose of crime prediction at precise spatial temporal scales. To rectify the issue of irregular and sparse crime information in local spatial temporal contexts, the model used a periodic periodic integral mapping. Its purpose was to record the time-space correlations of three types of crime data: recent, near-historical, and distant-historical, and to characterize the spatial differences in the contributions of these correlations. At last, thorough testing on Los Angeles-based real-world datasets proved that the suggested ST3DNetCrime framework outperforms baseline techniques in terms of prediction performance and improved robustness.

Tasnim et al. [13] presented an Attention-LSTM (ATTN-LSTM) and Stacked Bidirectional LSTM (St-Bi-LSTM) based framework for crime prediction across multiple districts and cities. The dataset consisted of categorical, temporal, and spatial information, which was pre-processed and relevant features were selected based on correlation. The ATTN-LSTM model processed categorical-temporal data, while the St-Bi-LSTM handled spatial information to capture location-specific crime patterns. To address the variability of feature distributions across different cities, Feature-Level Fusion (FLF) and Decision-Level Fusion (DLF) parts were incorporated. The proposed approach aimed to forecast crime efficiently than existing methods by leveraging temporal sequences and location-specific trends. However, prediction accuracy may be affected when training on cities with significantly different data distributions.

Rayhan and Hashem [14] presented an Attention based Interpretation Spatio-Temporal model (AIST) for crime prediction. The adaptive spatio-temporal relationship correlations were applied to analyze the crime classes using the external factors such as crime vehicular movement and location data, repeated crime patterns and real crime records. The characteristics were inputted into AIST in order to capture the complex and dynamic and non-sequentialconnections of environmental reliance and temporal aspects for predicting a certain type of crime. Overfitting problems have merged as a result of insufficient data interpretation.

Zhou et al. [15] created a Hybrid Dynamic Multi-Perspective Graph Neural Network (HDM-GNN) to detect the crime actions. This approach leverages Spatio and temporal interactions using varied urban data and incorporates the inter-regional relations across various perspectives. The compressive spatial trends and extensive temporal interactions were obtained using the Gated CNN and Graph Attention model. But, this model struggles with training spatiotemporal features from diverse sequences and effectively fusing complementary features.

Wang et al. [16] introduced a Spatial Temporal Multivariate Zero-Inflated Negative Binomial Graph Neural Networks (STMGNN-ZINB) method. In order to parameterize probability distributions of criminal occurrences, this paradigm uses convolution and diffusion networks to examine geographical, temporal, and multivariate relationships. To improve prediction accuracy and confidence interval precision, STMGNN-ZINB uses a Zero-Inflated Negative Binomial technique to handle sparse crime data. Testing on real-world datasets has shown that STMGNN-ZINB is superior to other models, making it a more trustworthy resource for studying and forecasting criminal behavior.

Wang et al. [17] developed a crime occurrence prediction model with multi-type crime correlation learning called Multi-Type Relations Aware Graph Neural Networks (MRAGNN). This model uses dynamic graph networks to capture the data's spatio-temporal and type-temporal connections, and it builds a spatial/type graph structure of the crime data dynamically. The two dependents' representations were fused using a cross-modal controlled fusion technique. The problems caused by the imbalance in the data on crime occurrences on classification results were finally addressed by applying an enhanced multi-label classification focus loss. However, the model's inability to adequately address imbalance concerns resulted in less accurate results"

III. PROPOSED METHODOLOGY

In this part explains the proposed GCN-GRU model for crime prediction in detail. Figure 1 depicts the pipeline of the suggested technique.

➢ *Mathematical Definition of Crime Prediction Task*

A variety of spatiotemporal parameters, including incident type, time, longitude, and latitude, are systematically used to capture crime data. By utilizing a sliding window technique, the input data may be expressed as a multidimensional vector $X \in R^{R*T*C}$, where R is the number of regions, T is the length of the time window, and C is the number of crime types. In each element X of the set R^{R*T*C} the count of crime type c in region r during time frame t is indicated. The following is a possible formulation of the task: The aim is to forecast the numbers of various crime kinds in each area at time T + 1, given the input $X \in R^{r*t*c}$. The outcome is $Y \in R^{(R*C)}$.

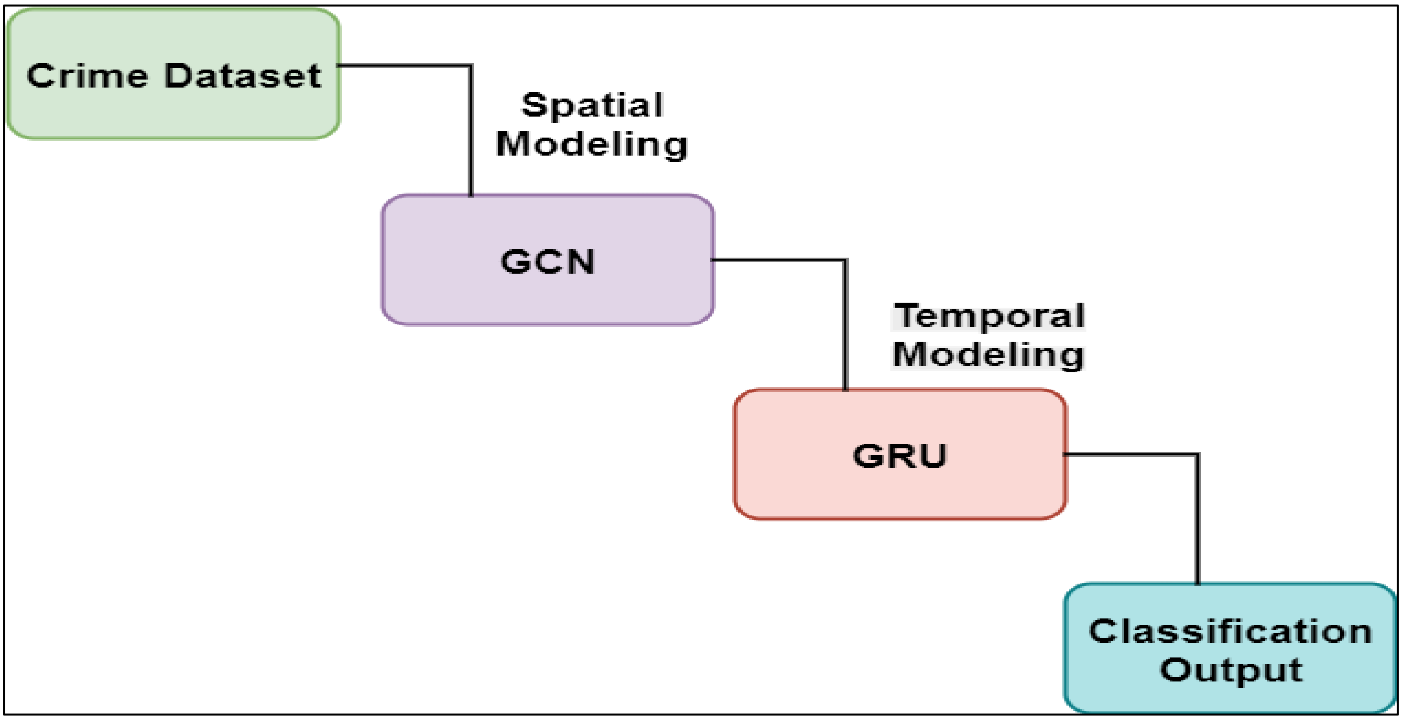

Fig 1 Pipeline of The Suggested Study

➢ *GCN*

To efficiently use the fundamental connections among nodes for robust feature extraction, GCNs—a specialized type of CNNs—are trained to work directly on graph-structured data [18]. Complex data patterns and interdependencies can be better captured by GCNs than by typical statistical methods [19]. So, to find patterns in the crime data and extract geographical features, GCN was chosen for this investigation. The graph data is transformed into a tensor representation after processing by the GCN. Figure 2 shows the computational workflow, which may be represented by the following equations:

$$\tilde{A}=A+I \qquad (1)$$

$$\tilde{D}_{ii}=\sum_j \tilde{A}_{ij} \qquad (2)$$

$$H^{(l+1)}=\sigma\left(\tilde{D}^{(1/2)}\tilde{A}\tilde{D}^{(1/2)}H^l\omega^l\right) \qquad (3)$$

Here, H^l signifies the input features at layer l, σ represents the sigmoid function, A denotes the adjacency matrix capturing the relations among nodes, ω^l signifies the trainable weight variables at l and D represents the diagonal degree matrix (typically utilized in the computation of the Laplacian matrix).

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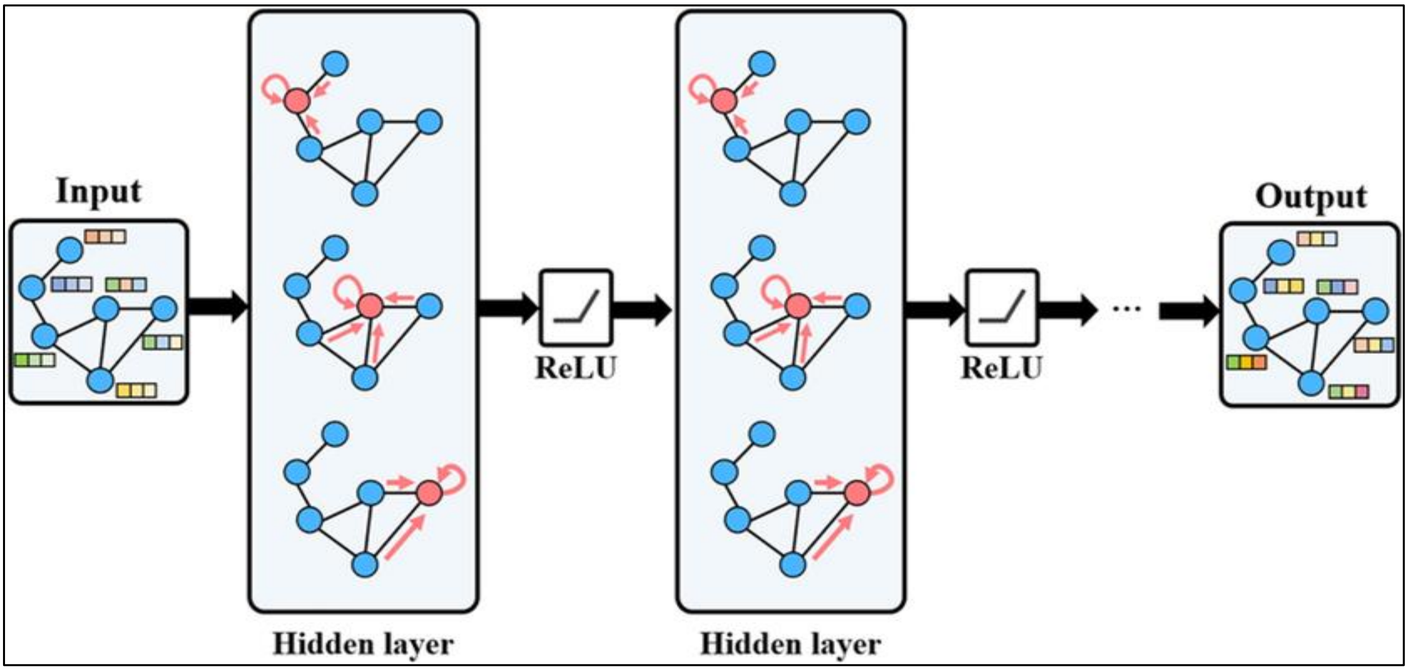

Fig 2 Architecture of GCN

➢ *Proposed Model of GCN-GRU*

The entire structure of the GCN-GRU model is outlined in Figure 3. The training process is then performed as follows: In the first step, previous-day crime records are aggregated together with a sliding window of a grid-based solution, the result will be a matrix with daily time resolution as the model input. The feature learning module is then used to learn reliable cross-task features that are found and transferred as inputs to the prediction module to predict the crime incidence in the next day. The two main components of the GCN-GRU design are the feature extraction and prediction modules.

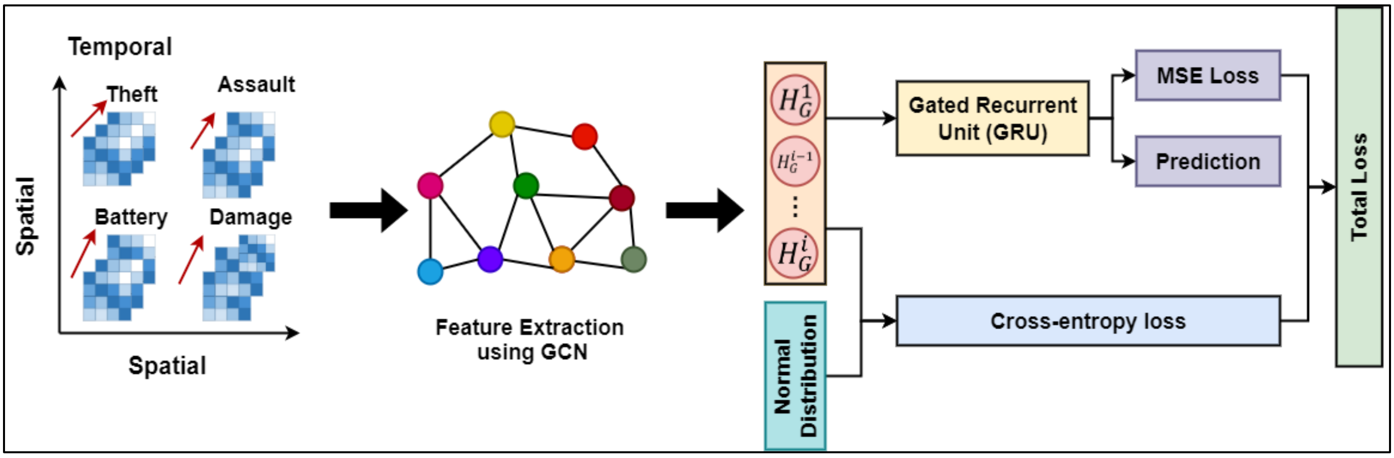

Fig 3 Architecture of GCN-GRU Technique

➢ *Feature Extraction Module*

The crime spatiotemporal data is initially handled through a sliding window mechanism to convert them into a supervised learning format. Since the crime data contains spatial dependencies, they are captured with the help of GCNs which extract detailed spatial features. The feature extraction module output, which is referred to as HG is presented as:

HG = GCN (X, A) (4)

In (4), *X* indicates the input data.

➢ *Prediction Module*

The relational mechanism in the GRU framework is implemented to compute and refresh the relationships between crime categories and geographic regions. A full computational procedure is shown in Fig. 4. Computation of GRU layers can be illustrated as below equations.

The update gate z_t is computed as in (5)

z_t= σ(W_z (h_(t-1),x_t)+b_z) (5)

In (6) is used to calculate the reset gate r_t

r_t= σ(W_r (h_(t-1),x_t)+b_r) (6)

In (7) is used to calculate the candidate hidden state $\hat{h}_t$

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$$\hat{h}_t=\tanh(W_h.[r_t \odot h_{(t+1)},x_t]+b_h) \quad (7)$$

Finally, the hidden state h_t representing the temporal embedding is updated by

$$h_t=(1-z_t)\odot h_{(t+1)}+z_t \odot \hat{h}_t \quad (8)$$

Where, x_t and h_t represents the input feature vector and a hidden state at the regression cycle t, respectively. W_z, W_r, W_h is the weight parameter of the update gate, reset gate and candidate hidden state, and b_z, b_r, b_h represents the bias parameter of the corresponding one. The activation function is represented by σ ,while element-wise multiplication is denoted by $\odot$. Figure 4 depicts the GRU architecture.

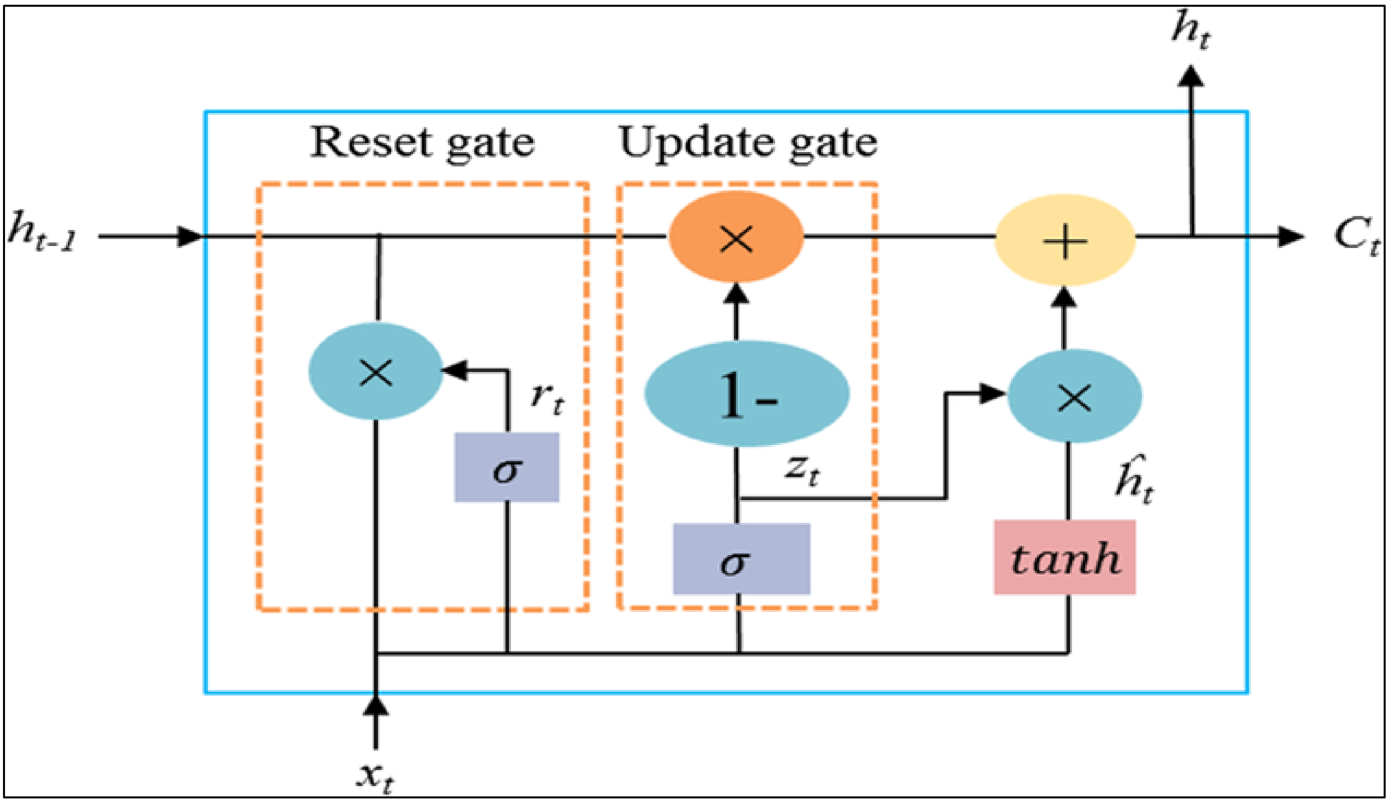

Fig 4 Architecture of GRU

➢ *Loss Function*

Using the ideas outlined in [20], they include a cross-entropy loss in the model to enhance the accuracy of classification in predicting crime category. This approach assigns different importance weights to each category based on their occurrence frequency in the training dataset, thus addressing class imbalance and increasing the technique's simplification ability. The formulation of the cross-entropy loss is the following one.

$$L_{CE}(Y,\hat{Y})=-1/N \sum_{i=1}^{N} \sum_{c=1}^{N} \propto_c \hat{y}_{i,c} \log(\hat{y}_{i,c}) \quad (9)$$

Where, N indicates the amount of samples, C denotes the quantity of crime categories, $\hat{y}_{i,c}$ represents the binary indicator (0 or 1) which is made 1 when sample i falls in category c, $\hat{y}_{i,c}$ denotes the forecast vision that sample i falls in category c, and $\propto_c$ is the adaptive weight for category c.

The adaptive weight $\propto_c$ is calculated as:

$$\propto_c = 1/(\log(\beta+p_c)) \quad (10)$$

where p_c specifies the percentage of samples belonging to sort ccc in the training set, and $\beta > 1$ is a smoothing factor to prevent extremely large weights.

In addition to the classification objective, an approach to quantifying the discrepancy between anticipated and observed crime rates is the Mean Squared Error (MSE) cost:

$$L_{MSE}(Y,\hat{Y})= 1/N \sum_{i=1}^{N} (y_i-\hat{y}_i)^2 \quad (11)$$

Finally, the overall loss function is described by:

$$\text{Total loss}= L_{MSE}+ \lambda.L_{CE} \quad (12)$$

In (11), Y signifies the predicted output, $\hat{Y}$ denotes the true label, L_{MSE} indicates the mean squared error loss, L_{CE} denotes the cross-entropy loss, and $\lambda \in (0,1)$ is a balancing coefficient that controls the contribution of the classification loss relative to the regression loss.

➢ *Model Training*

The GCN-GRU model for crime prediction is trained using the optimal hyperparameters summarized in Table 1. In addition, crime predictions using the acquired data can be accurately made using the trained model.

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Table 1 Parameter Settings

Parameters	**Range**
No. of GRU layers	2
Kernel Size	8
Filter Size	98
Pool Size	5
No. of GCN layers	2
GRU Output Size	128
Dropout	0.4
Momentum	0.9
Regulation term	1.0
Batch size	64
Epochs	100
Learning rate	0.01
Optimizer	Adam
Loss function	Cross Entropy
Activation function	ReLU / Tanh

IV. RESULTS AND DISCUSSION

➢ *Dataset Description*

The set of data employed in this framework is 'Crime in India' [21], which provides comprehensive information on various categories of crimes that occurred in India from 2001 onwards. Multiple factors can be analyzed from this dataset, enabling individuals to gain deeper insights into India's crime statistics. It comprises 43 sections covering different types of crimes. Some data include district-level details such as police districts and special police units, which may vary from revenue districts. The majority of the records span the years 2001 to 2010, with certain files extending to 2011 and 2001–2014. For experimental analysis, four major crime classes are considered: 'ST_SCcrime,' 'Childcrime,' 'Womencrime,' and 'Theftcrime.' Additionally, image and video data related to crime terminologies from social media tweets corresponding to these four classes are collected. By associating each crime record with its respective image and video content, a total of 9,794 crime instances are obtained for experimentation.

➢ *Experimental Design and Evaluation Metrics*

Comparing the GCN-GRU technique in Python 3.11 to other methods like NAHC[11], ST-3DNet[12], STMGNN-ZINB[16], and MRAGNN[17], this unit determines how well the GCN-GRU technique performs. The tests were performed on a Windows 10 (64-bit) machine with an Intel® Core™ i5-4210 CPU running @ 3GHz, 4GB of RAM, and a 1TB Hard disk drive. In both cases, the proposed and baseline models were evaluated using the datasets outlined in Section 4.1. From the processed data, a total of 9,794 samples were identified, of which 7,834 were allocated for training and 1,960 for testing, following an 80:20 split.

The following performance measures are used to assess the technique's capability to predict criminal conduct.

- *Accuracy*:

It is the percentage of occurrences for which predictions were accurate divided by the overall amount of cases.

$$Accuracy= (TP + TN)/ (TP+TN+FP + FN) \tag{13}$$

Where, A true positive (TP) occurs when the model accurately labels an occurrence as a criminal offense. A false positive (FP) occurs when the model mistakenly labels an occurrence that is not a criminal as a crime. If the model accurately predicts that an occurrence will not be a crime, we say that it is a true negative (TN). When a crime is mistakenly predicted by the model as a non-crime, it is called a false negative (FN).

- *Precision:*

It quantifies the proportion of TP predictions (accurately anticipated criminal events) relative to the total number of positive predictions generated by the model.

$$Precision=TP/(TP+FP) \tag{14}$$

- *Recall*:

It finds the fraction of correct predictions relative to the total number of positive occurrences in the dataset.

$$Recall=TP/(TP+FN) \tag{15}$$

- *F1-score:*

A score that finds an ideal balance between recall and precision.

$$F1\text{-}score=(2\times Precision\times Recall)/(Precision+Recall) \tag{16}$$

Fig 5 shows the comparison of the performances of various crime prediction models using the Crime in India dataset. The precision of GCN-GRU model is 5.42%, 4.16%, 2.81%, and 1.6% higher over the NAHC, ST-3DNet, STMGNN-ZINB and MRAGNN models, respectively. In terms of recall, GCN-GRU shows improvements of 4.3%, 3.84%, 2.83% and 1.5% over the same models. Additionally, the F1-score of GCN-GRU is higher by 5.41%, 4.15%, 2.8%, and 1.59% over the same models, respectively. These enhancements are attributed to the model's effective feature extraction and sequential pattern learning in crime prediction.

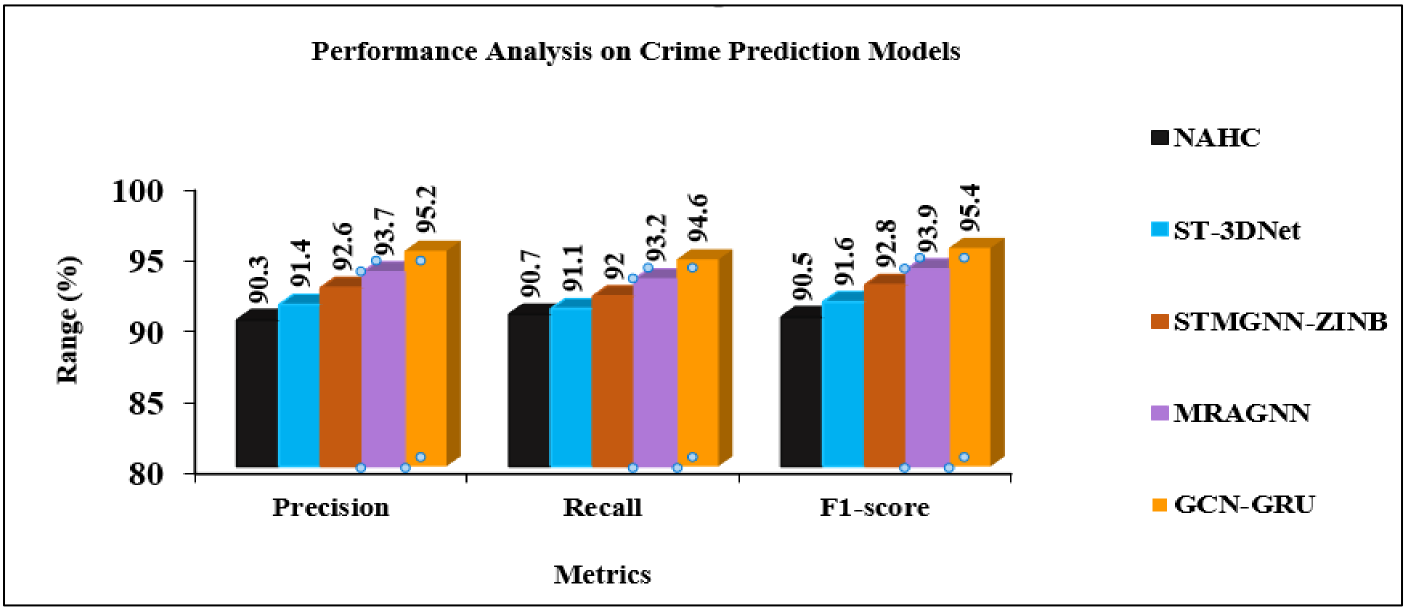

Fig 5 Performance Analysis of Different Crime Prediction Models

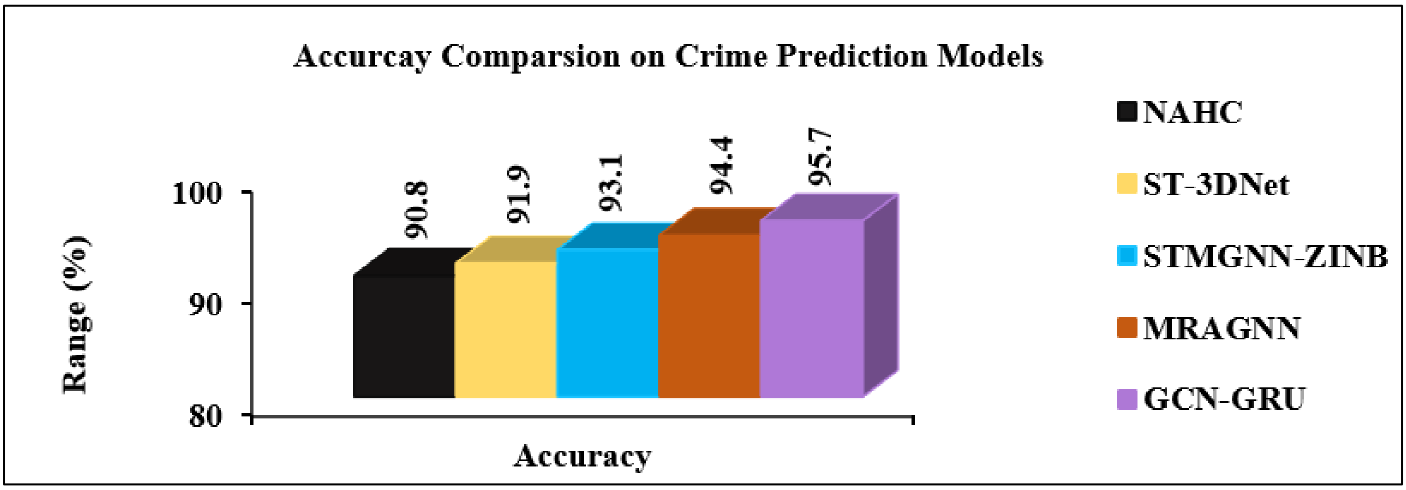

Fig 6 Accuracy Analysis of Different Crime Prediction Models

Fig 6 illustrates the accuracy of various models evaluated on the crime data prediction dataset. The GCN-GRU model achieves accuracy that is 5.39% higher than NAHC, 4.13% higher than ST-3DNet, 2.79% higher than STMGNN-ZINB, and 1.38% higher than MRAGNN. This enhancement is due to which the GCN-GRU model maximizes the prediction accuracy compared to the other models by effectively learning complex features from the historical and social media information to predict crime intensities precisely.

V. CONCLUSION

This study proposes the GCN-GRU technique to enhance crime prediction by addressing the limitations of traditional LSTM and GCN architectures. This model uses a GCN based mechanism to dynamically update the graph topology, improving spatial feature extraction across diverse and noisy crime data regions. The GCN component ensures resilience by capturing both local and global dependencies while reducing overfitting to fixed neighborhood structures. In the temporal dimension, the GRU network, with its reset and update gates, reduces computational complexity, improves memory efficiency, and effectively models both long-term and sudden short-term crime variations. Additionally, the integration of the Cross-Entropy Loss function strengthens classification accuracy by assigning higher probabilities to correct crime categories. By combining these mechanisms, the GCN-GRU model achieves efficient spatial-temporal feature learning and reduces computational cost. Finally, experimental results confirm that the GCN-GRU model surpasses existing crime prediction approaches, delivering higher accuracy and adaptability for real-world crime forecasting.

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