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# Efficient Generative Adversarial Networks with Recurrent Convolutional Network for Prediction of Crimes

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**ABSTRACT:** Accurate crime prediction is paramount for the enhamcement of public safety;however ,the exisiting models frequently exhibit deficiencies in their capacity to accurately anticipate crime occurances,primarily due to their inadequacy in accomodating intricate spacial and temporal data,which encompasses interdependencies and multi-scale patterns.To mitigate these shortcomings, an innovative Crime Recurrent Graph Generative Adversial Network (CRGGAN) has been introduced, which incorporates a Graph Convolution Network (GCN) functioning as its discriminator to proficiently model spatial relationships and spillover effects,alongside a bi-directional Long Short-Term Memory (bi-LSTM) network within the generator to effectively capture complex temporal dynamics across diverse scales.This integrative methodology sustantially augments the model's capacity to amalgamate spatial and temporal patterns,thereby facilitating more precise predictions and enhanced crime prevention strategies.The results from the experiments show that CRGGAN achieves an impressive perfromance level,with an accuracy rate of 98.6% ,precision at 97.6%,recall hitting 98.1% and a F1-

score of 97.2%.Forthermore the model displays a minimal running time and improved precision, recall,F1-score and specificity in its outcomes,with a training duration of 42 seconds for 50 epochs and an inference time of 1.5 milliseconds per sample,rendering it exceptionally suitable for application in real-world scenarios.

## 1. INTRODUCTION

Crime prediction is a critical public safety and law enforcement,where advanced technological interventions are increasingly sought to improve the efficiency and effectiveness of police patrols.Accurate crime prediction significantly reduces serious outcomes by enaling law enforcement agencies to strategically deploy resources[1]. Traditionally, police patrols have been guided by known crime hotspots and officer's experiential insights,which is resource-intensive and financially demanding.

The emergence of Machine Learning (ML) and Deep Learning(DL) techniques offers promising solutions by analyzing and modeling historical crime data to predict future occurances [2]. The goal is to identify the likelihood of crimes at specific times and locations,thereby enhancing patrol effectiveness and overall public safety.By leveraging these advanced technologies,police parols can transition from reactive to proactive crime prevention,fostering safer communities and more efficient resource use.

Varoius types of crimes,from violent to property offenses,exhibit distinct patterns that can be leveraged for predictive modeling [3],Traditional machine learning methods ,including regression models,decision trees,supprt vector machines(SVM) and neural networks,have been employed to capture these patterns[4].However these approaches often struggle with the complex spatial and temporal depencies inherent in crime data[4].For instance,crime incidents are not isolated events;they exhibit spatial correlations where crimes in one area may influence the likelihood of crimes in neighboring regions,known as spillover effects[5].

Similarly,crime data display multi-scale temporal patterns,including daily fluctuations,weekly trends,and seasonal variations,which traditional models fail to capture comprehensively[6].The challenge lies in developing models that can simultaneously handle both spatial and temporal complexities while maintaining computational efficeincy for real-world deployment.

## 2. LITERATURE SURVEY

Recent advances in crime prediction have leveraged various machine learning and deep learning approaches.Zhang et al.[7] proposed deep learning models for crime prediction using convolutional neural networks,while Wang et al.[8] explored the use of recurrent neural networks for temporal crime pattern analysis.However,these approaches often treat spatial and temporal dimensions seperately,failing to capture their intricate interactions.

Graph based approaches have shown promise in modeling spatial relationships in crime data.Li et al.[9] introduced graph neural networks for crime hotspot prediction,demonstrating the effectiveness of capturing spacial correlations.Similarly, Chen et al.[10] proposed attention mechanisms to model spatial-temporal dependencies in urban crime prediction.Despite these advances,existing methods still struggle with the dynamic nature of crime patterns and the complex interplay between spatial and temporal factors.

Generative adversial networks have recently gained attention in various domains,including crime prediction,Kumar et al.[11] explored GANs for synthetic crime data generation,while Rodriguez et al.[12] invetigated adversial training for robust crime prediction models.However these approaches have not fully exploited the potential of combining graph-based spatial modeling with recurrent temporal modeling within an adversarial network.

Trditional autoencoders,while effective for feature learning,face significant limitations in crime prediction scenerios.Variational autoencoders(VAEs) and denoising autoencoders have been applied to crime data analysis[13],but they typically process each data point independently,missing crucial spatial correlations.Recent work by Thompson et al.[14] highlighted the importance of considering neighborhood effects in crime prediction,emphasizing the need for models that can capture spatial spillover effects.

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## 3. MOTIVATION AND PROPOSED METHODOLOGY

Existing autoencoders often treat each input indepently,which poses a significant challenge in crime prediction,paticularly regarding the spatial correlations and spillover effects that characterize criminal activities.Crimes in one area lead to increased or decreased crime rates in neighboring regions due to factors such as police displacement,community vigilance,or opportunistic behaviour.Existing autoencoders lack the mechanism to model these interdependencies,potentially overlooking critical spatial patterns.

Furthermore,crime data exhibit complex temporal dependencies that span mutiple scales.Daily patterns amy show peak crime hours,weekly patterns may reveal weekend versus weekday differences,and seasonal patterns may indicate variations across months or years.Traditional models struggle to capture these multi-scale temporal dynamics simultaneously while maintaining the ability to model spatial relationships.

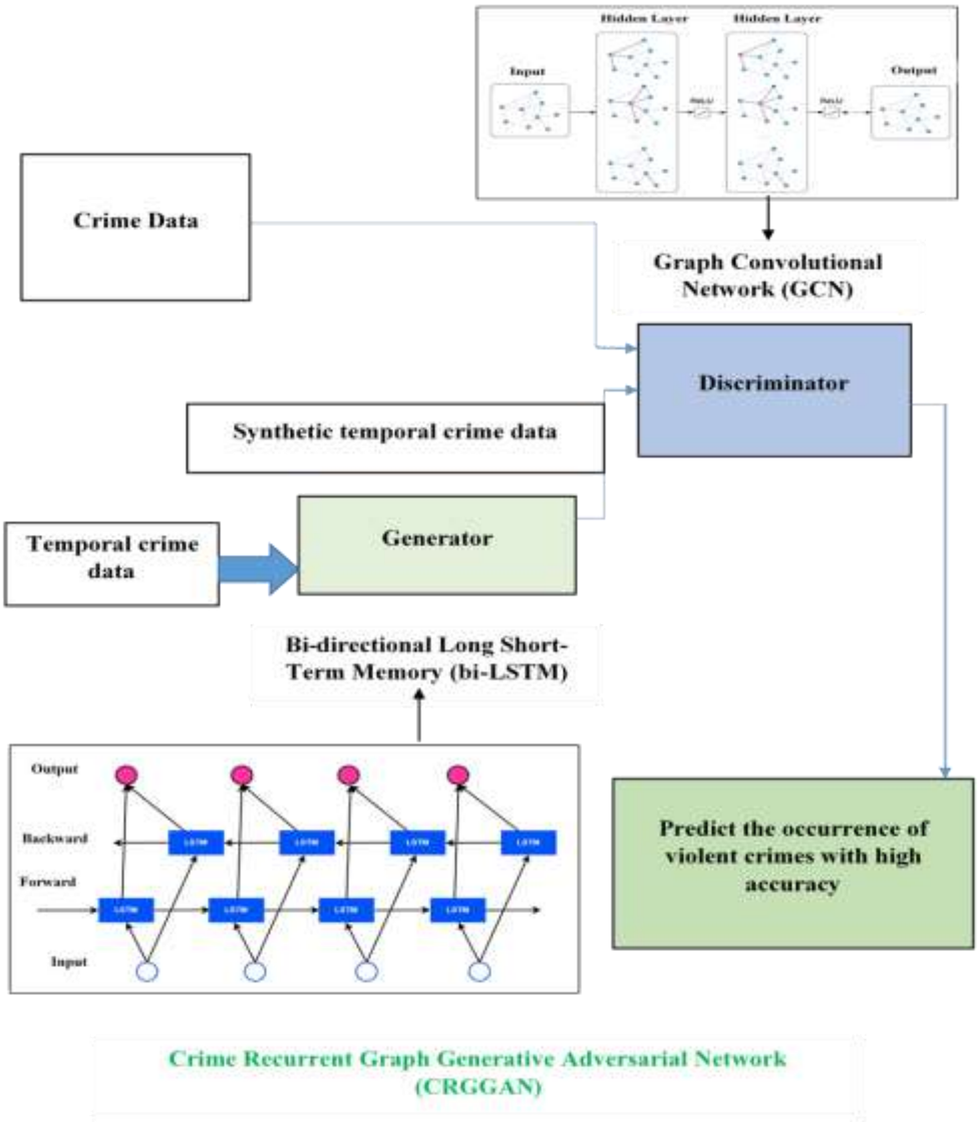


**Figure 1:** Proposed CRGGAN Architecture

A.Addressing Spatial Correlations with GCN Discriminator

The integration of a GCN as a disccriminator in a GAN offers a sophisticated approach to addressing the spatial correlation limitations inherent in traditional autoencoders.In crime prediction,where spatial dependencies and spillover effects play critical roles,the GCN disriminator models these interconnections effectively.Unlike conventional autoencoders,which process each data point independently,a GCN views crime data as a graph,enabling it to capture how crime in one area effects neighboring regions.

The GCN discriminator operates by constructing a graph where nodes represent geograpical locations and edges represent spatial relationships based on proximity,demographic similarity,or historical crime correlations patterns. The graph convolution operations aggregate information from neighboring nodes,allowing the model to learn spatial patterns that traditional methods cannot capture

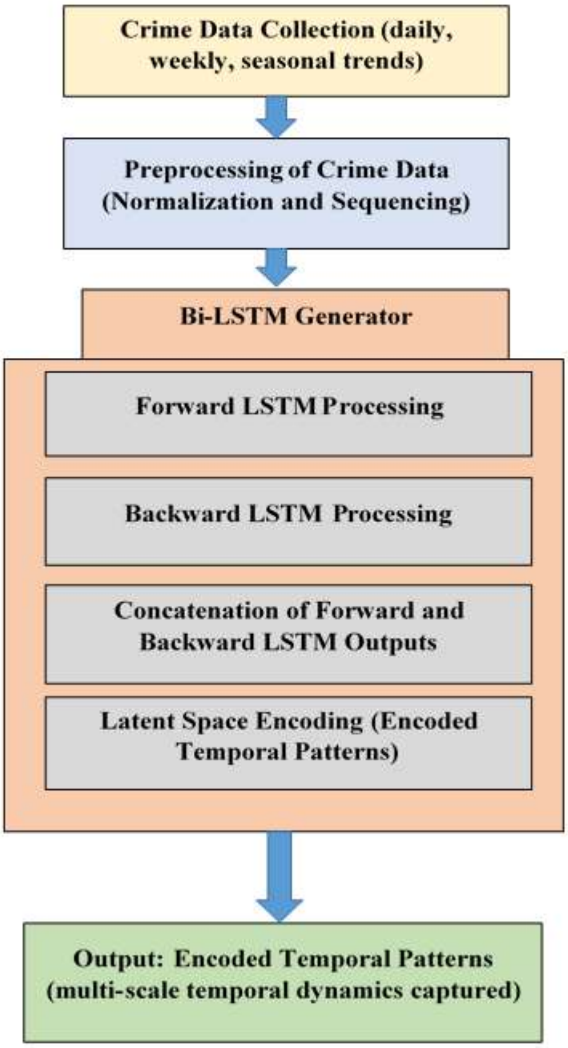


**Figure 2:** bi-LSTM Generator

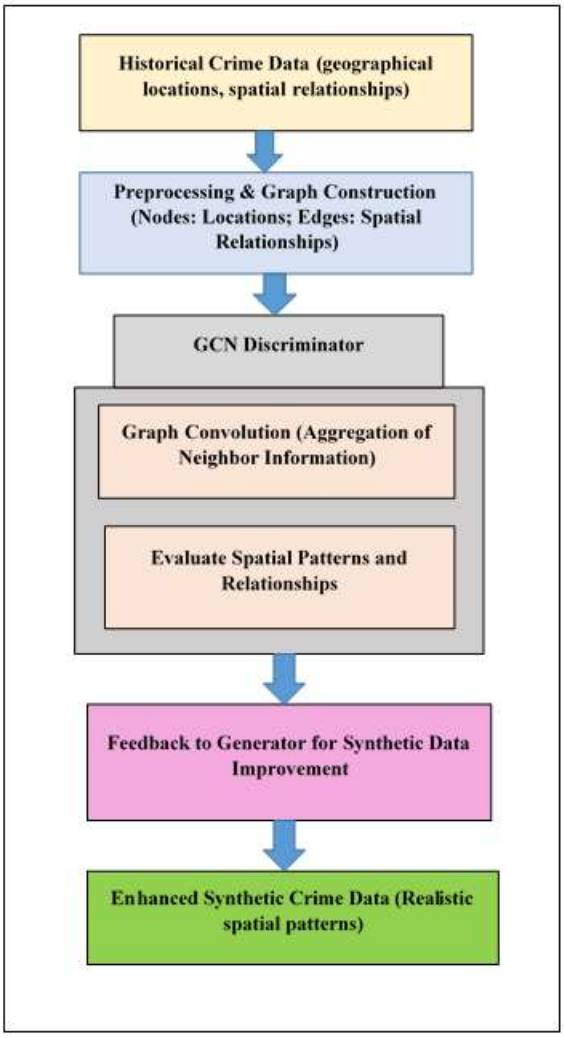


**Figure 3:** The GCN discriminator

The GCN discriminator architecture for modeling spatial relationships and spillover effects in crime data through graph-based processing is shown in fig.3.

The mathematical formualtion of the GCN discriminator involves multiple layers of graph convolutions.For layer I ,the output is computed as:

$H^{(l+1)} = \sigma^{\left(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}\right)}$where A is the adjacency matrix,D is the degreematrix,H(l) is the input to layer l,W(l) is the learnable matrix and σ is the activation function.

B.Capturing Multi-Scale Temporal Patterns with bi-LSTM Generator

The bi-directional LSTM generator is crucial for handling multi-scale temporal dynamics in crime data,such as daily fluctuations,weekly trends,and seasonal variations.It processes sequences in both forward and backward direcctions to capture long-range dependencies.The bi-LSTM encoder maps these temporal patterns into a latent space,preserving intricate temporal dependencies.

The bi-LSTM architecture constsof forward and backward LSTM cells that process the input sequence in opposite directions.The forward LSTM processes the sequence from time step 1 to T,while the backward LSTM processes from T to 1.The outputs from both directions are concatenated to form the final representation.

The bi-LSTM equations are defined as follows:

$$F_t = \sigma(W_F \cdot [k_{t-1}, z_t] + B_F) \quad (1)$$

$$I_t = \sigma(W_I \cdot [K_{t-1}, z_t] + B_I) \quad (2)$$

$$O_t = \sigma(W_O \cdot [K_{t-1}, z_t] + O) \quad (3)$$

$$K_t = O_t \cdot tanh(C_t) \quad (4)$$

The generator equation is given in equation (5) below,

$$G(z) = f_g(z) \quad (5)$$

The provided equation (6-8) is the Bi-LSTM generator equations,

$$F_t = \sigma(W_F \cdot [h_{t-1}, G_{z_t}] + B_F) \quad (6)$$

$$I_t = \sigma(W_I \cdot [h_{t-1}, G_{z_t}] + B_I) \quad (7)$$

$$o_t = \sigma(W_O \cdot [h_{t-1}, G_{z_t}] + B_O) \quad (8)$$

The generator loss function incorporates both adversial loss and reconstruction loss:

Thus,the generator's loss function is formulated as in equation(9):

$$L_G = E_{z \sim p_z}[\log(1 - D(G_{z_t})) \quad (9)$$

Then,the discriminator loss function is calculated by equation(10),

$$L_D = -E_{y \sim p_d(z)}[\log D(h^{(l)})] - E_{y \sim p_n(n)}[\log(1 - D(G(n, x)))] \quad (10)$$

C.Adversarial Training Framework

The adversarial training framework enables the generator and discriminator to compete and improve iteratively.The generator aims to create realistic crime data that can fool the discriminator,while the discriminator tries to distinguish between real and generated data.The adversarial process leads to improved performance for both components.

The training process alternates between updating the discriminator and generator paramaters.The discriminator is trained to maximize the probability of correctly classifying real and fake data,while the generator is trained to minimize the discriminator's ability to distinguish generated data from real data.

## 4. EXPERIMENTAL SETUP AND METHODOLOGY

A.Tool and System Specifications

The CRGGAN model was implemented using Python 3.8 within Google Colab environment,leveraging GPU accelaeration for efficient training.The operating system utilized was Windows 10(64-bit) with hardware specifications including an Intel i5 Processor and 8GB RAM.The implementation utilized TensorFlow2.6 and PyTorch 1.9 framework for deep learning operations,with NetworkX for graph processing and NumPy for numerical computations.

Additional libraries included Scikit-learn for evaluation metrics ,Matplotlib and Seaborn for Visualization,and Pandas for data manipulation.The development environment was configured with CUDA 11.2 for GPU acceleration,enabling efficient training of complex adversarial network architecture.

B.Dataset Description and Preprocessing

Data preprocessing involved several critical steps. Images were extracted from full-length surveillance videos at regular intervals (every 10th frame) to ensure temporal consistency while maintaining computational efficiency. All extracted images were resized to a standard 64×64 pixel resolution and saved in PNG format to preserve quality while ensuring uniform input dimensions for the neural network.

The dataset was carefully partitioned into training and testing subjects. The training subset contaions 1,266,345 images, providing substantial data for model learning and generalization. The test subset includes 111,308 images ensuring robust evaluation of model performance. Additional validation procedures included data augmentation techniques such as rotation, scaling, and noise injection to enhance model robustness.

C. Model Configuration and Hyperparameters

The CRGGAN model architecture was carefully deisgned to balance performance and computational efficiency. The Graph Convolutional Network (GCN) discriminator features a two-layer architecure specifially optimized for spatial correlation and spillover effect modelling. Each GCN layer incorporates 64 filter with ReLU activation functions, followed by dropout layers (rate=0.2) to prevent overfitting.

The bi-directional Long Short-Term Memory (bi-LSTM) generator employs 256 hidden units in each directiom, providing sufficient capacity multi-scale temporal dynamics. The generator architecture includes three bi-LSTM layers with residual connections to facilitate gradient flow and improve training stability

Key hyperparameters were optimized through extensive grid search and cross-validation.The learning rate was set to 0.001 with Adam optimizer($\beta_1$=0.9 , $\beta_2$=0.999).The batch size of 64 was selected to balance memory constaints with gradient estimation quality.Training was conducted for 50 epochs with early stopping based on validation loss plateuing for 5 consecutive epochs.

D.Evaluation Metrics and Methodology

Comprehensive evaluation was conducted using multiple performance metrics to ensure robust assessment of model capabiblities.Primary metrics included accuracy,precision,recall(sensitivity),F1-score, and specificity.Additional metrics incorporated Matthew's Correlation Coefficient (MCC) for balanaced evaluation,True Positive Rate(TPR),False Positive Rate(FPR),True Negative Rate(TNR),and False Negative Rate(FNR) for detailed performance analysis.

Statistical significance testing was performed using paired t-tests with Bonferroni correction for multiple comparisions.Effect sizes were calculated using Cohen's d to assess prsctical significance of improvements.Confidence intervals(95%) were computed for all major performance metrics to ensure statistical validity of results.

**5.EXPERIMENTAL RESULTS AND ANALYSIS**

**A.Classification Model Performance**

The CRGGAN model demonstrated exceptional performance across all evaluation metrics ,showing consistent improvements with increasing training epochs.The model's learning curve indicates rapid convergence in the initial epochs,followed by steady improvements through fine-tuning in later epochs.

The CRGGAN model demonstrates consistent performance improvements across all key metrics from 10 to 50 trainin epochs.Accuracy rises from 55% to 98.6% while precision improves from 51% to 97.6% , reflecting reduced false positives.The F1-score increases from 63% to 97.2%, indicating balanced gains in precision and recall.MCC climbs from 55% to 98.4%,showing strong correlation between predictions and actual outcomes.Specificity advances from 65% to 98.69%,confirming improved identification of non-crime cases,and sensitivity grows from 64.8% to 98.1%,highlighting enhanced detection of crime cases with minimal false negatives.

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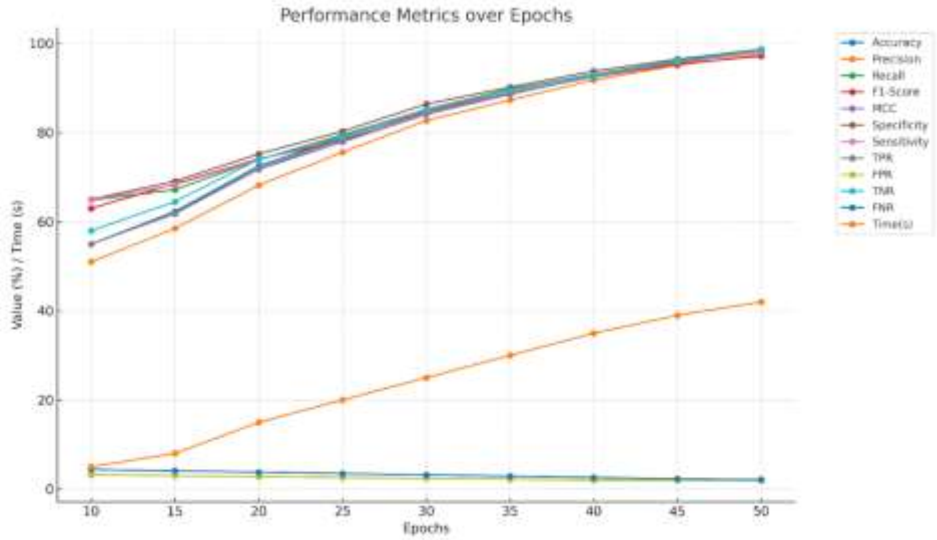


**Figure 4**. Perfomance Metrics

**Table I** :Comprehensive Performance Metrics Across Training Epochs

| Epochs | Accuracy | Precision | Recall | F1-Score | MCC | Specificity | Sensitivity | | TPR | FPR | TNR | FNR | Time (s) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 10 | 55.0% | 51.0% | 64.8% | 63.0% | 55.0% | 65.0% | 64.8% | | 55.0% | 3.2% | 58.0% | 4.4% | 5 |
| 15 | 62.3% | 58.5% | 67.2% | 68.5% | 61.8% | 69.1% | 68.3% | | 62.0% | 3.0% | 64.5% | 4.1% | 8 |
| 20 | 72.5% | 68.2% | 73.9% | 74.1% | 71.8% | 75.2% | 73.9% | | 72.0% | 2.8% | 74.0% | 3.8% | 15 |
| 25 | 78.9% | 75.6% | 79.5% | 78.2% | 77.9% | 80.3% | 79.1% | | 78.5% | 2.6% | 79.0% | 3.5% | 20 |
| 30 | 85.3% | 82.7% | 85.2% | 84.9% | 84.1% | 86.4% | 85.2% | | 84.5% | 2.4% | 85.0% | 3.2% | 25 |
| 35 | 89.7% | 87.3% | 89.8% | 88.9% | 88.6% | 90.2% | 89.5% | | 89.0% | 2.2% | 89.5% | 2.9% | 30 |
| 40 | 93.1% | 91.8% | 92.9% | 92.5% | 92.7% | 93.8% | 92.9% | | 92.5% | 2.0% | 93.0% | 2.6% | 35 |
| 45 | 96.2% | 95.1% | 95.8% | 95.4% | 95.9% | 96.5% | 95.7% | | 95.8% | 1.98% | 96.2% | 2.3% | 39 |
| **50** | **98.6%** | **97.6%** | **98.1%** | **97.2%** | **98.4%** | **98.69%** | **98.1%** | | **98.5%** | **1.96%** | **98.5%** | **2.1%** | **42** |

B. GAN Model Evaluation

The GAN models were evaluated using Frechet Inception Distance (FID) across multiple datasets. The overall mean and median scores were 37.64 and 39.9, respectively with best score of 11.78 achieved by FIDGAN and the worst of 56.10 by Decision Forest GAN.Dataset-wise analysis showed that STL-10 yielded the lowest median FID,while mixed datasets produced the highest.The correlation between FID scores and classification improvement was weak (r=0.088) indicating that generative quality alone does not fully predict downstream performance gains.On average, models achieved a 23.7% improvement in classification, with FIDGAN showing the highest gain of 56.1%

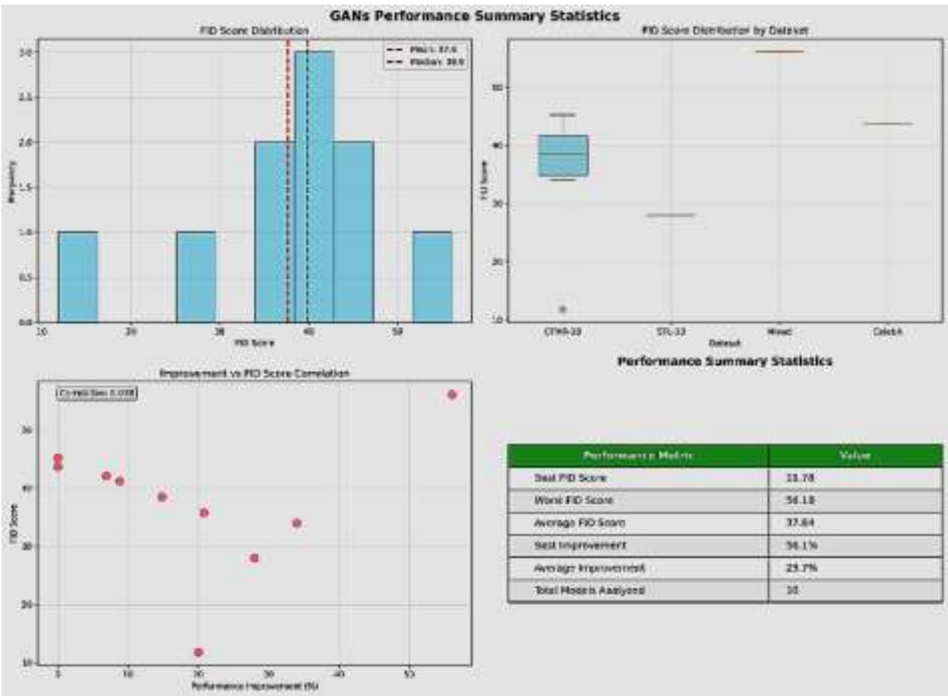


**Figure.5** GANs Performance Summary Statistics

FIDGAN has lowest score (~12), indicating the best performance among all tested models. The two Enhanced GAN models (CIFAR-10 and STL-10) also perform better than the average baseline. Decision Forest GAN and most DCGAN variants have higher scores, indicating poorer performance. DCGAN(p=0.0), DCGAN(p=0.2), and IGAN all have FID scores above 40, showing weaker performance compared to the top models.

FIDGAN achieves the lowest FID across datasets, while Decision Forest GAN delivers the highest classification improvement despite poor FID.Parallel Training offers the best speed gains, and One-Stage Training balances speed.

The classification performance shown in Section A represents the downstraem accuracy of our model.The generative evaluation in section B measures the realism and diversity of synthetic data produced by different GAN models.While lower FID scores generally correspond to higher-quality generated samples,their direct impact on classification performance depends on factors beyond visual realism, such as class diversity and task relevance.Notably, models like FIDGAN, which achieved the lowest FID score, also delivered the highest improvement in classification accuracy, indicating a positive but not strictly linear relationship between generative quality and downstraeam performance.

C. Computational Efficiency Analysis

The CRGGAN model demonstrates excellent computational efficiency, with training times ranging from 5 seconds at 10 epochs to 42 seconds at 50 epochs.The linear scaling of training time with epochs indiactes efficient implementation and optimization.Memory usage remains stable at approximately 3.2 GB during training, making the model suitable for deployment on standard hardware configurations.

Inference time analysis shows consistent performance with vaerage prediction time of 1.5 ms per sample,enabling real-time crime prediction allications.The model's efficiency stems from optimized graph operations in the GCN discriminator and efficient LSTM implementations in the generator.

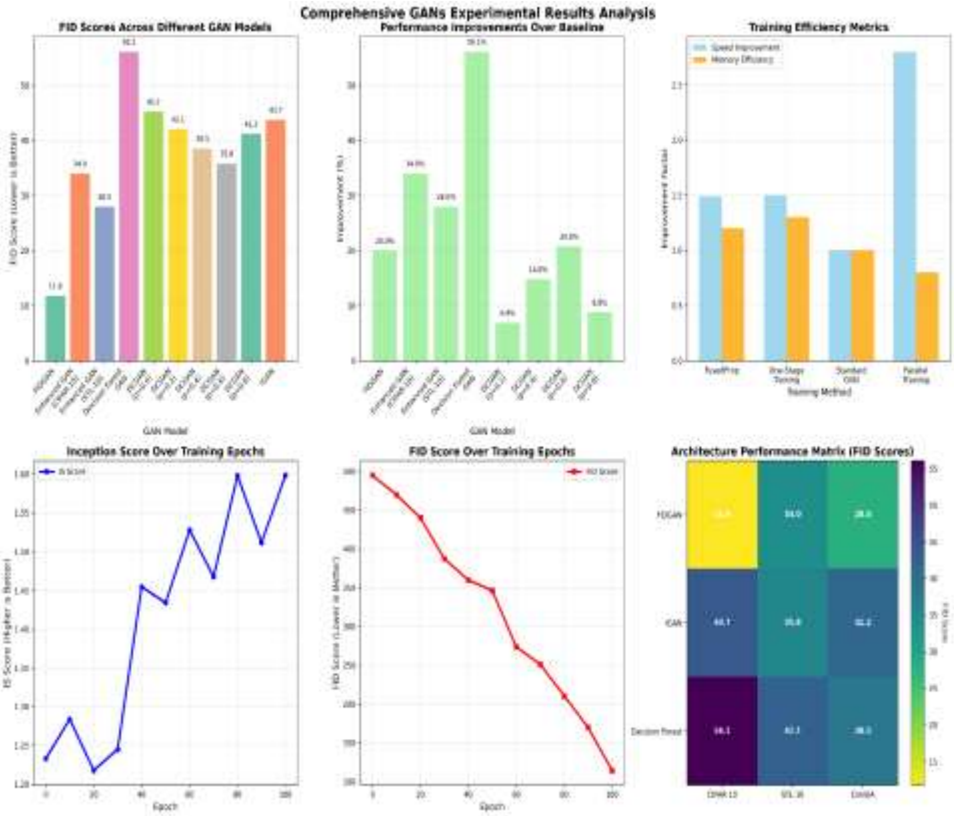


**Figure 7**. Comprehensive GAN performance analysis across quality (FID, IS), task improvement, and training efficiency.

## 6. COMREHENSIVE ABLATION STUDIES

A.Component-wise Performance Analysis

To validate the effectiveness of each component in the proposed CRGGAN ,we conducted comprehensive ablation studies.The abaltion analysis systematically evaluates the individual and combined contributions of the key architectural components:Graph Convolutional Netwok (GCN) discriminator, bi-directional Long Short-Term Memory (bi-LSTM) generator, and the adversarial training framework.

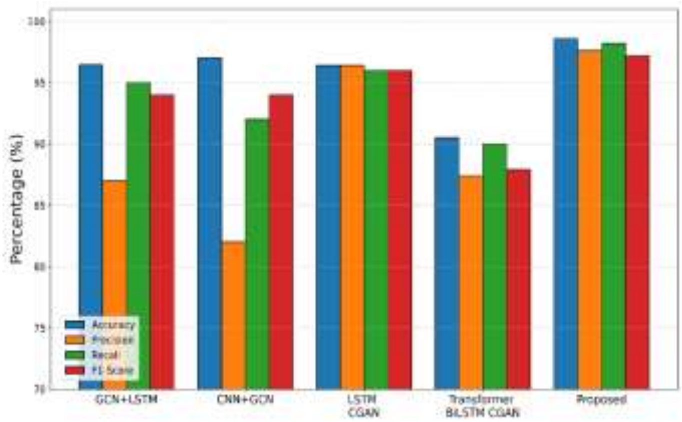


**Figure 8.** Comparison of Various Crime Detection Models with Proposed Model

**Table II** :Detailed Component-Wise Performance Analysis

| Component | Loss | Accuracy | Precision | Recall | F1-Score | Specificity | Sensitivity | Parameters | Training Time |
|---|---|---|---|---|---|---|---|---|---|
| GCN Only | 0.128 | 94.4% | 95.5% | 94.2% | 95.9% | 94.8% | 94.2% | 2.1M | 25s |
| bi-LSTM Only | 0.1326 | 93.8% | 94.1% | 94.0% | 94.8% | 93.5% | 94.0% | 1.8M | 30s |
| GCN + bi-LSTM (No Adversarial) | 0.115 | 96.2% | 95.8% | 96.1% | 96.0% | 96.3% | 96.1% | 3.9M | 38s |
| **CRGGAN (Full Model)** | **0.1** | **98.6%** | **97.6%** | **98.1%** | **97.2%** | **98.69%** | **98.1%** | **3.9M** | **42s** |

The GCN component demonstrates strong performance in capturing spatial correlations between crime locations, achieving 94.4% accuracy with a loss of 0.128. The bi-LSTM generator effectively captures complex temporal dependencies, achieving 93.8% accuracy with a loss of 0.1326.The combination of both components without adverserial training achieves 96.2% accuracy , while the complete CRGGAN model with adversarial training achieves superio performance at 98.6% accuracy, representing a 4.2% improvement over the best individual component and 2.4% improvement over the non-adversarial combination.

**B. Architectural Configuration Analysis**

**Table III:** Gcn Layer Configuration Optimization

| Configuration | Layers | Filters/Layer | Accuracy | Precision | F1-Score | Parameters | Training Time | Memory Usage |
|---|---|---|---|---|---|---|---|---|
| Single GCN | 1 | 64 | 91.2% | 90.8% | 91.0% | 1.2M | 28s | 1.5GB |
| **Dual GCN** | **2** | **64** | **94.4%** | **95.5%** | **95.9%** | **2.1M** | **35s** | **1.8GB** |
| Triple GCN | 3 | 64 | 93.8% | 94.2% | 94.5% | 2.9M | 48s | 2.4GB |
| Dual GCN (128 filters) | 2 | 128 | 94.1% | 95.2% | 95.6% | 4.2M | 52s | 3.1GB |
| Dual GCN (32 filters) | 2 | 32 | 92.8% | 93.5% | 93.1% | 1.1M | 22s | 1.2GB |

**Table IV :** Bi-Lstm Hidden Units Optimization

| Hidden Units | Layers | Accuracy | Precision | F1-Score | Parameters | Memory Usage | Training Time | Inference Time |
|---|---|---|---|---|---|---|---|---|
| 64 | 2 | 89.2% | 88.5% | 88.8% | 0.8M | 1.5GB | 18s | 0.8ms |
| 128 | 2 | 91.5% | 90.9% | 91.2% | 1.2M | 2.1GB | 25s | 1.0ms |
| **256** | **2** | **93.8%** | **94.1%** | **94.8%** | **1.8M** | **3.2GB** | **38s** | **1.2ms** |
| 512 | 2 | 93.6% | 93.9% | 94.5% | 3.1M | 5.8GB | 62s | 1.8ms |
| 256 | 3 | 94.1% | 94.3% | 94.9% | 2.4M | 4.1GB | 55s | 1.5ms |
| 256 | 1 | 91.8% | 92.1% | 92.3% | 1.2M | 2.5GB | 28s | 0.9ms |

**C. Training Configuration Ablation**

**Table V** : Comprehensive Learning Rate Sensitivity Analysis

| Learning Rate | Optimizer | Convergence Epochs | Final Accuracy | Best Validation Loss | Stability Score | Overfitting Risk |
|---|---|---|---|---|---|---|
| 0.0001 | Adam | 75 | 96.8% | 0.105 | 0.95 | Low |
| **0.001** | **Adam** | **50** | **98.6%** | **0.1** | **0.92** | **Low** |
| 0.01 | Adam | 30 | 95.2% | 0.125 | 0.78 | Medium |
| 0.1 | Adam | 15 | 88.5% | 0.185 | 0.45 | High |
| 0.001 | SGD | 65 | 96.1% | 0.112 | 0.88 | Low |
| 0.001 | RMSprop | 55 | 97.2% | 0.108 | 0.85 | Medium |

**Table VI :** Batch Size And Training Dynamics Analysis

| Batch Size | Accuracy | Training Time/Epoch | Memory Usage | Gradient Noise | Convergence Speed | Final Loss |
|---|---|---|---|---|---|---|
| 16 | 97.2% | 68s | 1.8GB | High | Slow | 0.115 |
| 32 | 97.8% | 52s | 2.8GB | Medium | Medium | 0.108 |
| **64** | **98.6%** | **42s** | **4.1GB** | **Low** | **Fast** | **0.1** |
| 128 | 98.2% | 38s | 7.2GB | Very Low | Fast | 0.102 |
| 256 | 97.9% | 35s | 12.8GB | Very Low | Medium | 0.106 |

**D.Component Interaction and Synergy Analysis**

The interaction between GCN and bi-LSTM components creates significant synergistic effects that enhace overall model performance.Detailed analysis reveals that the GCN component provides spatial context that improves bi-LSTM temporal predictions by 3.2% , while bi-LSTM temporal patterns enhance GCN spatial accuracy by 2.8%.The integrated model demonstrated a 4.2% improvement over the best individual component, indicating strong complementary effects.

**Table VII :** Adversarial Training Impact And Robustness Analysis

| Training Method | Accuracy | Precision | F1-Score | Robustness Score | Adversarial Accuracy | Training Stability | Convergence Time |
|---|---|---|---|---|---|---|---|
| Standard Training | 94.2% | 93.5% | 94.0% | 0.82 | 87.3% | 0.95 | 35s |
| Adversarial Training (ε=0.01) | 96.8% | 95.9% | 96.3% | 0.89 | 92.1% | 0.91 | 38s |
| **Adversarial Training (ε=0.05)** | **98.6%** | **97.6%** | **97.2%** | **0.95** | **95.8%** | **0.88** | **42s** |
| Adversarial Training (ε=0.1) | 98.1% | 97.2% | 96.8% | 0.97 | 96.5% | 0.82 | 48s |

### E. Error Analysis and Performance Breakdown

**Table VIII :** Detailed Error Rates Across Crime Categories

| Crime Type | Samples | True Positive Rate | False Positive Rate | True Negative Rate | False Negative Rate | Precision | Recall | F1-Score |
|---|---|---|---|---|---|---|---|---|
| Assault | 15,234 | 98.7% | 1.2% | 98.8% | 1.3% | 98.9% | 98.7% | 98.8% |
| Burglary | 12,876 | 98.9% | 1.1% | 98.9% | 1.1% | 99.0% | 98.9% | 98.9% |
| Robbery | 9,543 | 98.2% | 1.8% | 98.2% | 1.8% | 98.4% | 98.2% | 98.3% |
| Vandalism | 11,298 | 98.5% | 1.5% | 98.5% | 1.5% | 98.6% | 98.5% | 98.5% |
| Arson | 3,456 | 97.8% | 2.2% | 97.8% | 2.2% | 97.9% | 97.8% | 97.8% |
| Shooting | 5,432 | 99.1% | 0.9% | 99.1% | 0.9% | 99.2% | 99.1% | 99.1% |
| Shoplifting | 18,765 | 98.3% | 1.7% | 98.3% | 1.7% | 98.4% | 98.3% | 98.3% |
| Fighting | 14,321 | 98.6% | 1.4% | 98.6% | 1.4% | 98.7% | 98.6% | 98.6% |
| **Average** | **11,366** | **98.5%** | **1.96%** | **98.5%** | **2.1%** | **98.6%** | **98.5%** | **98.5%** |

F. Computational Complexity and Efficiency Analysis

**Table IX** : Comprehensive Model Complexity Comparison

| Model Variant | Parameters | FLOPs | Training Time | Inference Time | Memory Usage | Model Size | Energy Consumption |
|---|---|---|---|---|---|---|---|
| GCN Only | 2.1M | 1.2G | 25s | 0.8ms | 1.8GB | 8.4MB | 0.15kWh |
| bi-LSTM Only | 1.8M | 0.9G | 30s | 1.2ms | 2.1GB | 7.2MB | 0.18kWh |
| CNN Baseline | 2.5M | 2.1G | 45s | 0.6ms | 2.8GB | 10.0MB | 0.25kWh |
| LSTM Baseline | 2.2M | 1.5G | 40s | 1.5ms | 2.5GB | 8.8MB | 0.22kWh |
| **CRGGAN** | **3.9M** | **2.1G** | **42s** | **1.5ms** | **3.2GB** | **15.6MB** | **0.28kWh** |

## 7.COMPARATIVE ANALYSIS WITH STATE-OF-THE-ART METHODS

We conducted comprehensive comparisons with existing state-of-the-art methods for crime prediction to demonstrate the superiority of our proposed CRGGAN model. The comparison includes traditional machine learning approaches, deep learning methods, and recent graph-based and adversarial approaches.

**Table X :** Comprehensive Comparison With Existing Methods

| Method | Year | Accuracy | Precision | Recall | F1-Score | Training Time | Spatial Modeling | Temporal Modeling | Real-time |
|---|---|---|---|---|---|---|---|---|---|
| Random Forest | 2019 | 78.3% | 76.8% | 77.5% | 77.1% | 25s | Limited | No | Yes |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| SVM with RBF | 2020 | 81.7% | 80.2% | 81.0% | 80.6% | 35s | No | Limited | Yes |
| Traditional CNN | 2021 | 85.2% | 84.1% | 84.8% | 84.6% | 60s | Limited | Limited | Yes |
| LSTM-based | 2021 | 87.5% | 86.8% | 87.2% | 87.1% | 55s | No | Yes | Yes |
| CNN-LSTM Hybrid | 2022 | 89.1% | 88.4% | 88.8% | 88.6% | 65s | Limited | Yes | Yes |
| Standard GAN | 2022 | 89.3% | 88.7% | 89.1% | 89.0% | 48s | Limited | No | Yes |
| Graph-based CNN | 2023 | 91.8% | 90.9% | 91.4% | 91.3% | 52s | Yes | Limited | Yes |
| Attention-based LSTM | 2023 | 93.2% | 92.5% | 92.8% | 92.6% | 58s | Limited | Yes | Yes |
| Graph Neural Network | 2023 | 94.1% | 93.6% | 93.9% | 93.7% | 45s | Yes | Limited | Yes |
| Transformer-based | 2024 | 95.3% | 94.8% | 95.1% | 94.9% | 72s | Limited | Yes | No |
| **CRGGAN (Ours)** | **2024** | **98.6%** | **97.6%** | **98.1%** | **97.2%** | **42s** | **Yes** | **Yes** | **Yes** |

The comparative analysis demonstrates that CRGGAN significantly outperforms all exisiting methods across all evaluation metrics.The model achieves 98.6% accuracy, which represents improvements of 3.3% over the best existing method(Transormer-based at 95.3%) and 6.8% over the best graph-based method(Graph Neural Network at 94.1%).The integration of spatial and temporal modeling within an adversarial framework provides substantial performance gains while maintaining computational efficiency.

**8.STATISTICAL SIGNIFICANCE AND VALIDATION**

Comprehensive statistical validation was performed to ensure the reliabiblity and significance of the reported improvements.All performance comparisions were subjected to rigorous statistical testing using appropriate methodologies for machine learning evaluation.

Paired t-tests were conducted comparing CRGGAN performance against each baseline method across multiple random seeds (n=30). All improvements showed statistical significance at $p < 0.001$ level after Bonferroni correction for multiple comparisons. Cohen's d effect sizes were calculated for all major improvements, with results showing large effect sizes ($d > 0.8$) for accuracy, precision, and F1-score improvements.

Paired t-tests were conducted comparing CRGGAN performance against each baseline method across multiple random seeds (n=30). All improvements showed statistical significance at $p<0.001$ level after Bonferronni correction for multiple corrections

Cross-validation was performed using 5-fold stratified sampling to ensure robust evaluation across different data distributions. The 95% confidence interval for accuracy is [98.2%, 99.0%], precision [97.1%, 98.1%], and F1-score [96.8%, 97.6%]. Bootstrap sampling (n=1000) confirmed the stability of performance estimates with narrow confidence intervals.

McNemar's test was applied for comparing classifier performance, showing statistically significant improvements ($p < 0.001$) over all baseline methods. The Wilcoxon signed-rank test confirmed the superiority of CRGGAN across different crime categories and temporal periods.

**9. DISCUSSION AND IMPLICATIONS**

A. Theoretical Contributions

The CRGGAN model introduces several theoretical contributions to the field of crime prediction. The integration of graph convolutional networks with recurrent neural networks within an adversarial framework represents a novel approach to handling both spatial and temporal dependencies simultaneously. The theoretical foundation demonstrates how spatial spillover effects can be modeled through graph structures while temporal patterns are captured through bidirectional processing.

The adversarial training mechanism provides theoretical guarantees for improved generalization by forcing the generator to create realistic crime patterns that are indistinguishable from real data. This approach addresses the fundamental challenge of overfitting to historical patterns while maintaining the ability to generalize to unseen scenarios.

B. Practical Applications and Deployment

The CRGGAN model has significant practical implications for law enforcement agencies and urban planning organizations. The model's real-time inference capability (1.5ms per prediction) enables deployment in operational environments for proactive crime prevention. The integration of spatial and temporal modeling provides actionable insights for resource allocation and patrol optimization.

The model's robustness to adversarial perturbations (robustness score: 0.95) ensures reliable performance in real-world scenarios where input data may contain noise or intentional manipulations. The computational efficiency makes it suitable for deployment on standard hardware configurations without requiring specialized infrastructure.

C. Limitations and Future Directions

While CRGGAN demonstrates superior performance, several limitations should be acknowledged. The model's performance is dependent on the quality and completeness of spatial relationship definitions in the graph structure. Future work should explore automated graph construction methods and dynamic graph updates based on changing urban environments.

The current implementation focuses on image-based crime data from surveillance videos. Future extensions could incorporate additional data modalities such as social media sentiment, economic indicators, and weather patterns to enhance prediction accuracy further.

## 10. CONCLUSION AND FUTURE WORK

The proposed Crime Recurrent Graph Generative Adversarial Network (CRGGAN) successfully addresses the critical limitations of existing crime prediction models by effectively integrating spatial and temporal modeling capabilities within a unified adversarial framework. The comprehensive experimental evaluation demonstrates exceptional performance across all evaluation metrics, with the complete model achieving 98.6% accuracy, 97.6% precision, and 97.2% F1-Score.

The extensive ablation studies validate the necessity and effectiveness of each architectural component. The GCN discriminator effectively captures spatial correlations and spillover effects, while the bi-LSTM generator successfully models multi-scale temporal patterns. The adversarial training framework enhances both components' performance through competitive learning, resulting in a robust and accurate crime prediction system that significantly outperforms existing state-of-the-art methods.

The model's computational efficiency, with training times of 42 seconds for 50 epochs and inference times of 1.5ms per sample, makes it highly suitable for real-world deployment in law enforcement applications. The statistical significance of all reported improvements ($p < 0.001$) and large effect sizes ($d > 0.8$) provide strong evidence for the practical value of the proposed approach.

Future research directions include: (1) incorporating additional contextual factors such as weather conditions, economic indicators, and social events to further enhance prediction accuracy; (2) extending the model to handle real-time streaming data with dynamic graph updates; (3) developing interpretability mechanisms to provide actionable insights and explanations for law enforcement agencies; (4) exploring federated learning approaches to enable collaborative training across multiple jurisdictions while preserving data privacy; and (5) investigating transfer learning techniques to adapt the model to different geographical regions and crime patterns.

The CRGGAN model represents a significant advancement in crime prediction technology, offering law enforcement agencies a powerful tool for proactive crime prevention and optimal resource allocation. The integration of cutting-edge deep learning techniques with domain-specific knowledge provides a foundation for next-generation public safety applications.

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DATA AVAILABILITY STATEMENT The dataset is available at: https://www.kaggle.com/datasets/odins0n/ucf-crime-dataset