International Journal of Multidisciplinary Engineering in Current Research - IJMEC
Volume 10, Issue 6, June-2025, http://ijmec.com/, ISSN: 2456-4265

Risk Prediction Of Theft Crimes Using Lstm And St Gcn

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ABSTRACT

Growing population increasing urbanization which will give rise to growing communities and will increase risk of crimes. Increasing crime will put people's security at risk and make difficult for security professional to maintain law and order. To tackle crime in growing urban communities' author of this paper employing combination of two different algorithms such as LSTM (long short-term memory) and GCN (Graph Convolution Network). LSTM is known to perform better prediction on temporal features like Date & Time and GCN known for best prediction on Spatial Features like Location. Combination of both LSTM & GCN can automatically and effectively detect the high-risk areas in a city. Topological maps of urban communities carry the dataset in the model, which mainly includes two modules such as spatial & temporal features extraction module and temporal feature extraction module to extract the factors of theft crimes collectively. To train and test above algorithm performance author has utilized US crime and Chicago Crime datasets and then for spatial features author has joined weather information like Temperature on Chicago dataset but this weather information extraction process we don't know so we have used Date & Time for LSTM temporal features training and Crime locations as Spatial features training with GCN. Propose algorithm performance in terms of R2square, RMSE and MAPE. R2square consider as accuracy for crime rate prediction model and then RMSE (root mean square error) and MAPE (mean absolute percentage error) represents difference between true and predicted crime rate. So the lower the difference the better is the algorithm. Combination of propose LSTM & GCN algorithm is known as ST-GCN and compare this propose algorithms performance with existing algorithms like Random Forest and LSTM. Among all algorithms propose is giving high R2score and less RMSE and MAPE.

***Keywords**: LSTM ,GCN , ST-GCN, RMSE , MAPE , R2_Score , Crime rate prediction , risk of increasing crimes.*

1-INTRODUCTION

Crime prediction and prevention are essential for ensuring public safety, urban planning, and law enforcement efficiency. Traditional crime forecasting models often rely on statistical techniques and heuristic-based approaches, which fail to capture the dynamic nature of crime patterns. With the rise of Artificial Intelligence (AI) and Machine Learning (ML), advanced predictive models can now analyze vast amounts of crime data, detect trends, and provide actionable insights to authorities.

The integration of deep learning algorithms such as Graph CNN, Bidirectional Networks, and Gated Recurrent Units (GRU) has revolutionized crime prediction. Unlike conventional models that only consider forward-moving data, these techniques allow for the analysis of bidirectional trends, ensuring better feature extraction and enhanced accuracy. Graph CNNs optimize data representation using graph-based structures, while Bidirectional layers process data from both past and future timelines to improve predictive reliability. GRU further refines the selected features and ensures efficient model training, making it an advanced alternative to traditional Long Short-Term Memory (LSTM) models.

Law enforcement agencies rely on predictive analytics to allocate resources, prevent criminal activities, and implement proactive strategies. Traditional methods, such as regression analysis, clustering, and decision trees, often suffer from limited accuracy, one-directional processing, and data loss. With AI advancements, deep learning-based crime forecasting models can now learn from historical crime data and detect patterns that were previously overlooked.

The proposed Graph CNN + Bidirectional + GRU model aims to overcome the shortcomings of existing LSTM-based models, ensuring a more efficient and transparent crime prediction framework. LSTM-based approaches primarily rely on forward-direction data, often omitting critical insights from past events, leading to a drop in accuracy. The Bidirectional layer in our model ensures that crime trends are analyzed from both past and future perspectives, optimizing prediction quality.Existing crime prediction models often struggle with feature selection, bidirectional data processing, and explainability.

2-LITERATURE SURVEY

F. Cicirelli, A. Guerrieri, G. Spezzano, and A. Vinci, An edge-based platform for dynamic smart city applications, Future Gener. Computer. System, vol. 76, pp. 106118, Nov. 2017.

A Smart City is a cyber–physical system improving urban behavior and capabilities by providing ICT-based functionalities. An infrastructure for Smart City has to be geographically and functionally extensible, as it requires both to grow up with the physical environment and to meet the increasing in needs and demands of city users/inhabitants. In this paper, we propose iSapiens, an IoT-based platform for the development of general cyber–physical systems suitable for the design and implementation of smart city services and applications. As distinguishing features, the iSapiens platform implements the edge through both the exploitation of the agent metaphor and a distributed network of computing nodes directly scattered in the urban environment.

The platform promotes the dynamic deployment of new computing nodes as well as software agents for addressing geographical and functional extensibility. iSapiens provides a set of abstractions suitable to hide the heterogeneity of the physical sensing/actuator devices embedded in the system, and to support the development of complex applications. The paper also furnishes a set of methodological guidelines exploitable for the design and implementation by properly using iSapiens. As a significant, the design and implementation of a real Smart Street in the city of Cosenza (Italy) are shown, which provides decentralized urban intelligence services to citizens.

M. A. Tayebi, M. Ester, U. Glässer, and P. L. Brantingham, CRIME TRACER: Activity spaced based crime location prediction, in Proc. IEEE/ACM Int. Conf. Adv. Social Network. Anal.

Crime reduction and prevention strategies are vital for policymakers and law enforcement to face inevitable increases in urban crime rates as a side effect of the projected growth of urban population by the year 2030.

Studies conclude that crime does not occur uniformly across urban landscapes but concentrates in certain areas. This phenomenon has drawn attention to spatial crime analysis, primarily focusing on crime hotspots, areas with disproportionally higher crime density. In this paper we present CRIMETRACER, a personalized random walk based approach to spatial crime analysis and crime location prediction outside of hotspots. We propose a probabilistic model of spatial behavior of known offenders within their activity territory, frequently commit opportunistic crimes and serial violent crimes by taking advantage of opportunities they encounter in places they are most familiar with as part of their activity space. Our experiments on a large real-world crime dataset show that CRIMETRACER outperforms all other methods used for location recommendation we evaluate here

H. Wang, D. Kifer, C. Graif, and Z. Li, Crime rate inference with big data, in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Aug. 2016, pp. 635644.

Crime is one of the most important social problems in the country, affecting public safety, children development, and adult socioeconomic status. Understanding what factors cause higher crime is critical for policy makers in their efforts to reduce crime and increase citizens' life quality. We tackle a fundamental problem in our paper: crime rate inference at the neighbourhood level. Traditional approaches have used demographics and geographical influences to estimate crime rates in a region. With the fast development of positioning technology and prevalence of mobile devices, a large amount of modern urban data have been collected and such big data can provide new perspectives for understanding crime. In this paper, we used large-scale Point-Of-Interest data and taxi flow data in the city of Chicago, IL in the USA. We observed significantly improved performance in crime rate inference compared to using traditional features. Such an improvement is consistent over multiple years. We also show that these new features are significant in the feature importance analysis.

Crawford and K. Evans, Crime prevention and community safety, Oxford Univ. Press, Oxford, U.K., Tech. Rep. 35, 2017.

This chapter traces and evaluates both the historic emergence of the modern ‘preventive turn’ as well as the elaboration and institutionalisation of crime prevention and community safety over the last thirty years or so. Focusing on the UK, the evolution and changes over time are situated, where relevant, in a broader international context. The chapter identifies three distinct periods of developments that structure the shifts in crime prevention policy and practices from the 1980s to the present day. It explores the conceptualisation, take-up and advancement of a preventive mentality and practices in relation to situational, social and developmental crime prevention as well as community safety. It goes on to assess the institutionalisation of preventive partnerships and early intervention as distinct forms of governance and their implications for ‘responsible’ and ‘securitisation’. In conclusion, it reflects upon the journey travelled thus far as well as possible future directions in an age of austerity.

X. Hu, J. Wu, P. Chen, T. Sun, and D. Li, Impact of climate variability and change on

crime rates in tangshan, China, Sci. Total Environ., vol. 609, pp. 10411048, Dec. 2017.

Studies examining the relation between climate and human conflict often focus on the role of temperature and have diverging views on the significance of other climatic variables. Using a 6-year (from 2009 to 2014) dataset of crime statistics collected in a medium size city of Tangshan in China, we find strong, positive correlations between temperature and both violent and property crimes. In addition, relative humidity is also positively correlated with Rape and Minimal Violent Robbery (MVR). The seasonal cycle is a significant factor that induces good correlations between crime rates and climatic variables, which can be reasonably explained by the Routine Activity theory. We also show that the combined impacts of temperature and relative humidity on crime rates can be reasonably captured by traditional heat stress indices. Using an ensemble of CMIP5 global climate change simulations, we estimate that at the end of the 21st century the rates of Rape (violent crime) and MVR (property crime) in Tangshan will increase by 9.5 ± 5.3% and 2.6 ± 2.1%, respectively, under the highest emission scenario (Representative Concentration Pathway 8.5). The gross domestic product (GDP) is also shown to be significantly correlated with MVR rates and the regression results are strongly impacted by whether GDP is considered or not.

M. Kassen, A promising phenomenon of open data: A case study of the chicago open data project, Government Inf. Quart., vol. 30, no. 4, pp. 508513, Oct. 2013.

This article presents a case study of the open data project in the Chicago area.

The main purpose of the research is to explore empowering potential of an open data phenomenon at the local level as a platform useful for promotion of civic engagement projects and provide a framework for future research and hypothesis testing. Today the main challenge in realization of any e-government projects is a traditional top–down administrative mechanism of their realization itself practically without any input from members of the civil society. In this respect, the author of the article argues that the open data concept realized at the local level may provide a real platform for promotion of proactive civic engagement. By harnessing collective wisdom of the local communities, their knowledge and visions of the local challenges, governments could react and meet citizens' needs in a more productive and cost-efficient manner.

Open data-driven projects that focused on visualization of environmental issues, mapping of utility management, evaluating of political lobbying, social benefits, closing digital divide, etc. are only some examples of such perspectives. These projects are perhaps harbingers of a new political reality where interactions among citizens at the local level will play a more important role than communication between civil society and government due to the empowering potential of the open data concept.

3- SYSTEM SPECIFICATIONS

The proposed crime risk prediction system employs a hybrid deep learning model combining Graph CNN, Bidirectional Layer, and GRU to enhance crime rate predictions. The methodology follows these key phases:

1. **Data Collection & Preprocessing:**

- Crime-related datasets are collected from government databases and Kaggle repositories.
- Data is cleaned, normalized, and augmented for model training.

2. **Feature Extraction & Model Training:**

- Graph CNN optimizes features using graph representations.
- Bidirectional Layer ensures feature importance from both forward and backward directions.
- GRU (Gated Recurrent Unit) refines selected features to improve accuracy.

3. **Model Evaluation & Comparison:**

- Metrics like R2 Score, MAPE, and RMSE are used for performance validation.
- The hybrid model outperforms traditional LSTM-based models in accuracy.

The unauthorized use of the words "Chicago Police Department," "Chicago Police," is unlawful. This web page does not, in any way, authorize such use. Data are updated daily. The dataset contains more than 6,000,000 records/rows of data and cannot be viewed in full in Microsoft Excel. To access a list of Chicago Police Department - Illinois Uniform Crime Reporting (IUCR) codes, go to http://data.cityofchicago.org/Public-Safety/Chicago-Police- Department-Illinois-Uniform-Crime-R/c7ck-438e

From Figure, we can see the proposed integrated model, which can be categorized into three modules spatial temporal feature extraction module, temporal feature extrac tion module, and feature integration module. First, the spatial-temporal feature extraction module is a combination of GCN and ST-GCN to extract the transition of crimes in space over time. Then, in order to detect crimes in each community, the temporal feature extraction module is built based on the LSTM network. Finally, the feature integration module employs GBDT model to integrate the predicted values from the spatial-temporal feature extraction module and the temporal feature extraction module.

Proposed system

Growing population increasing urbanization which will give rise to growing communities and will increase risk of crimes. Increasing crime will put people’s security at risk and make difficult for security professional to maintain law and order. To tackle crime in growing urban communities author of this paper employing combination of two different algorithms such as LSTM (long short term memory) and GCN (Graph Convolution Network). LSTM is known to perform better prediction on temporal features like Date & Time and GCN known for best prediction on Spatial Features like Location. Combination of both LSTM & GCN can automatically and effectively detect the high-risk areas in a city. Topological maps of urban communities carry the dataset in the model, which mainly includes two modules such as spatial & temporal features extraction module and temporal feature extraction module to extract the factors of theft crimes collectively.

To train and test above algorithm performance author has utilized US crime and Chicago Crime datasets and then for spatial features author has joined weather information like Temperature on Chicago dataset but this weather information extraction process we don’t know so we have used Date & Time for LSTM temporal features training and Crime locations as Spatial features training with GCN.

Author has evaluate propose algorithm performance in terms of R2square, RMSE and

MAPE. R2square consider as accuracy for crime rate prediction model and then RMSE (root mean square error) and MAPE (mean absolute percentage error) represents difference between true and predicted crime rate. So the lower the difference the better is the algorithm.

Combination of propose LSTM & GCN algorithm is known as ST-GCN and compare this propose algorithms performance with existing algorithms like Random Forest and LSTM. Among all algorithms propose is giving high R2score and less RMSE and MAPE.

4-METHODOLOGY

Data Collection

In this study on theft crime prediction in urban communities, data collection played a crucial foundational role. The primary dataset used was the *Chicago Crime Dataset*, obtained from Kaggle and originally published by the Chicago Police Department through their Open Data Portal. This dataset contains over six million records spanning from 2012 to 2017, and it is updated daily. Each entry in the dataset provides comprehensive details about individual crime incidents, including fields such as the date and time of occurrence, type and description of crime, location information, arrest status, community area identifier, and precise geographic coordinates (latitude and longitude). In addition to crime-specific data, supplementary contextual information was gathered to improve the robustness of the model. Weather data, including temperature and precipitation, was added to analyse the influence of seasonal variations on crime. Public holiday data was also incorporated to determine if crime rates fluctuate around special dates. Time-based variables such as time of day, day of the week, and month were engineered from the original date field.

Furthermore, socioeconomic factors like unemployment rates and poverty indices were included to provide insight into the underlying conditions of different community areas. To prepare the final dataset for model training, all relevant data sources were integrated using common fields such as date and community area. This created a rich, multi-dimensional dataset that combined crime records with environmental, temporal, and social context. Several validation steps were applied during preprocessing to ensure data quality. These included removing duplicate records, handling missing values, and detecting outliers (such as incorrect GPS coordinates). This thorough data collection and preprocessing strategy ensured that the model had access to high-quality inputs necessary for learning complex spatial-temporal patterns of theft crimes in urban settings.

Data Preprocessing

Once the raw data was collected, the next critical step was data pre-processing an essential phase to ensure the dataset is clean, consistent, and suitable for training machine learning models. Since the crime dataset contains a mixture of numerical, categorical, temporal, and geographic data, various preprocessing techniques were applied to handle different data types appropriately. Initially, the dataset was examined for missing values, which are common in large public datasets.

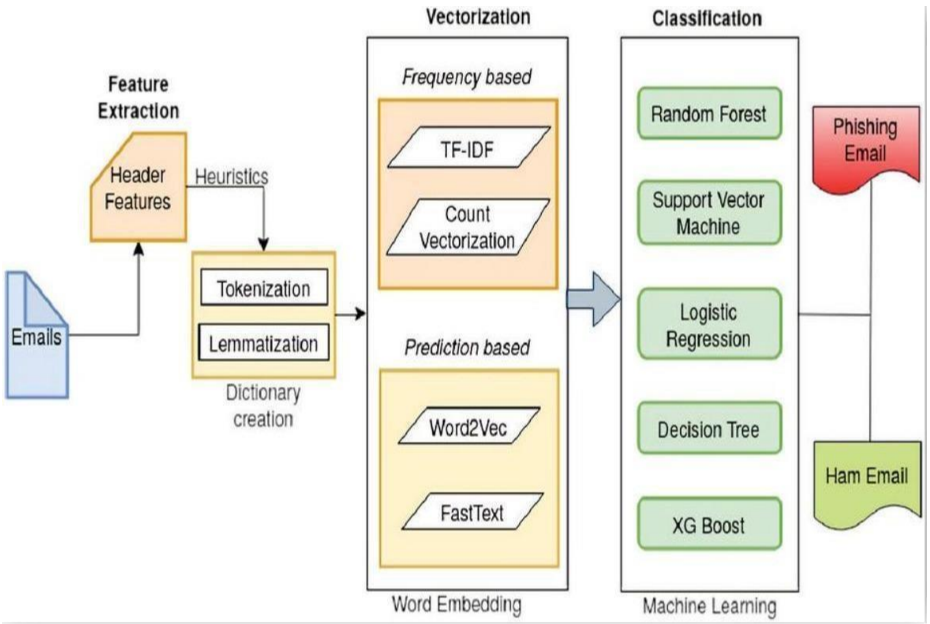

Figure 4.1 Data Preprocessing

These missing entries were either removed (if they were insignificant in volume) or imputed using statistical methods such as mean or mode substitution, depending on the feature type. Duplicate entries, if any, were also identified and eliminated to prevent biased learning. Next, categorical variables like crime type or location descriptions were converted into numeric formats using label encoding and one-hot encoding techniques, as machine learning algorithms typically require numerical input.

Temporal fields such as the date and time were processed to extract features like the hour of the day, day of the week, month, and whether the date was a holiday or weekend— providing crucial insights into time-based crime patterns. For location-related attributes, latitude and longitude values were retained as they offer geospatial context, while community area identifiers were treated as categorical numeric values.

To ensure that all numerical features had a uniform scale, normalization techniques were applied. Specifically, Min-Max normalization was used to scale all values into a 0–1 range. This step is particularly important for algorithms like neural networks and gradient-based methods, which are sensitive to the magnitude of input values. Outliers, especially in continuous variables like temperature or crime count, were also examined and capped or removed where necessary to maintain model stability.

Finally, the complete dataset was split into training and testing subsets, commonly using an 80-20 ratio. This division ensures that the model is trained on one portion of the data while being evaluated on unseen data, providing a realistic measure of predictive performance. This thorough and methodical data preprocessing pipeline significantly enhanced the model's ability to learn patterns effectively and produce reliable theft crime predictions.

Feature Selection:

Feature selection is a critical step in the development of an effective crime prediction model, as it directly influences the model's accuracy, efficiency, and interpretability. In this study, after collecting and preprocessing a large and diverse dataset comprising crime records, socioeconomic indicators, weather data, and time-related variables, feature selection was employed to identify the most relevant attributes for predicting theft crimes. The main goal of this process was to reduce dimensionality by eliminating redundant or irrelevant features, thereby enhancing model performance and minimizing computational cost. The selection process began with exploratory data analysis and visualization techniques such as correlation heatmaps and pair plots, which helped identify strong linear relationships between variables. Numerical correlation techniques, such as Pearson and Spearman correlation coefficients, were used to measure the strength and direction of associations between continuous features like temperature and crime frequency.

To further refine feature importance, tree-based ensemble models such as Random Forest and Gradient Boosting were employed, as they naturally rank features based on their contribution to reducing prediction error. These models not only provided insight into which features were most predictive of theft crimes but also helped discard noise-prone or weakly correlated attributes.

5-ALGORITHMS IN MACHINE LEARNING

In machine learning, an algorithm is a set of rules or procedures that a computer program follows to learn from data and make predictions or decisions. It's like a recipe that guides the program on how to process and analyze input data to produce desired outputs. Different algorithms are designed for specific tasks, such as classification, regression, clustering, or recommendation. Each algorithm has its own approach and mathematical principles to learn patterns and relationships in the data. By applying these algorithms to large datasets, machine learning models can make accurate predictions or discover meaningful insights. Machine learning (ML) is a field of computer science that has existed in theory for decades but have in recent years proven to be very useful in practice. Machine Learning is a subset of Artificial Intelligence (AI) that enables computers to learn from data and make decisions or predictions without being explicitly programmed. In the context of crime prediction, ML algorithms learn patterns from historical crime data to forecast future incidents, helping authorities take proactive measures.

Algorithms Used:

- Random Forest
- Logistic Regression
- Decision Trees
- Support Vector Machines (SVM)
- Gradient Boosted Decision Trees (GBDT)

Types of Algorithms: The algorithms that we have used in this project are:

1. **Random Forest:** The Random Forests classifier (RF) is a classifier that makes use of decision trees. It generates a large number of decision trees; each tree using a random number of samples and features from our data set. If classifiable data are input, the classifier returns the label that was decided on by the largest number of decision trees.

Random Forest algorithm is a powerful tree learning technique in Machine Learning. It works by creating a number of Decision Trees during the training phase. Each tree is constructed using a random subset of the data set to measure a random subset of features in each partition. This randomness introduces variability among individual trees, reducing the risk of overfitting and improving overall prediction performance. In prediction, the algorithm aggregates the results of all trees, either by voting (for classification tasks) or by averaging (for regression tasks) This collaborative decision-making process, supported by multiple trees with their insights, provides an example stable and precise results.

Random forests are widely used for classification and regression functions, which are known for their ability to handle complex data, reduce overfitting, and provide reliable forecasts in different environments. Random forest classifier is a machine learning algorithm used to classify applications as either phishing or non-phishing.

Random forest is known for its high accuracy and is used for phishing detection, as it works well with large datasets and can handle nonlinear relationships between features High accuracy: Random Forest models are known for their high accuracy and ability to handle noisy data.

2. Logistic Regression: Logistic Regression (LogReg) is a well-established statistical model for classifying data. It binarily classifies data by fitting the data points to a logistic function. The classifier is very powerful for simple, linearly separable data, but its performance starts to decline for data with complex relationships between variables. Logistic Regression is another commonly used algorithm for email phishing detection using machine learning. It has its own benefits and reasons for being used in this context:

6-SOFTWARE AND HARDWARE DESCRIPTION

Software requirements, also known as software requirements specifications (SRS), are a set of documented needs and expectations for a software system. These requirements define what the software should do, how it should behave, and what features and functionalities it should have. Software requirements are crucial for guiding the development process, ensuring that the software meets the desired objectives, and serving as a reference for testing and validation.

Software Requirements:

1. Programming Language:
- Python
2. Development Environment:
- Jupyter Notebook (used for coding and visualization)
- Python IDLE (optional for basic script execution)
3. Web Framework:

Hardware Requirements:

- Processor: Intel Core i5 (8th Gen or higher) or AMD Ryzen 5 equivalent
- RAM: 8 GB
- storage: 256 GB SSD (or HDD with ample space for datasets)
- Graphics: Integrated GPU (suitable for basic ML model training)
- Operating System: Windows 10 / Linux (Ubuntu preferred) / macOS

Python:

- One of the most popular languages is Python. Guido van Rossum released this language in 1991. Python is available on the Mac, Windows, and Raspberry Pi operating systems. The syntax of Python is simple and identical to that of English. When compared to Python, it was seen that the other language requires a few extra lines.
- It is an interpreter-based language because code may be run line by line after it has been

written. This implies that rapid prototyping is possible across all platforms. Python is a big language with a free, binary-distributed interpreter standard library.

- It is inferior to maintenance that is conducted and is straightforward to learn. It is an object-oriented, interpreted programming language. It supports several different programming paradigms in addition to object-oriented programming, including functional and procedural programming.

- It supports several different programming paradigms in addition to object-oriented programming, including practical and procedural programming. Python is mighty while maintaining a relatively straightforward syntax. Classes, highly dynamic data types, modules,

and exceptions are covered. Python can also be utilized by programmers that require programmable interfaces as an external language.

7-RESULTS AND IT'S DISCUSSION

Steps followed for the Result:

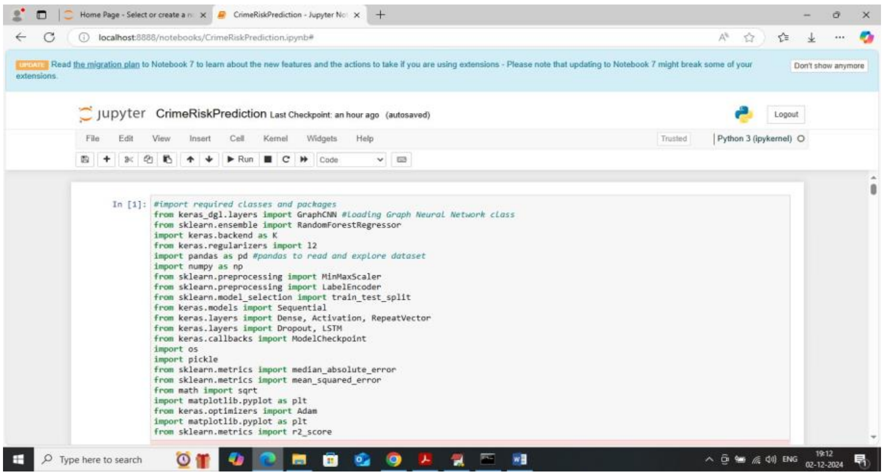

Figure 1 Importing required packages

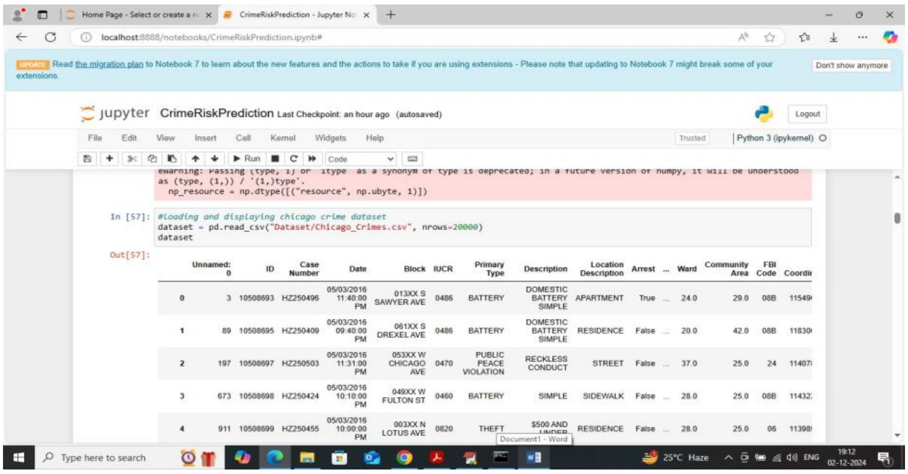

Figure 2 Loading and displaying 'Chicago Crime' dataset

In above screen loading and displaying 'Chicago Crime' dataset and can see dataset contains both numeric and non-numeric values but algorithms will take only numeric values so by employing dataset processing technique we need to convert all data to numeric format.

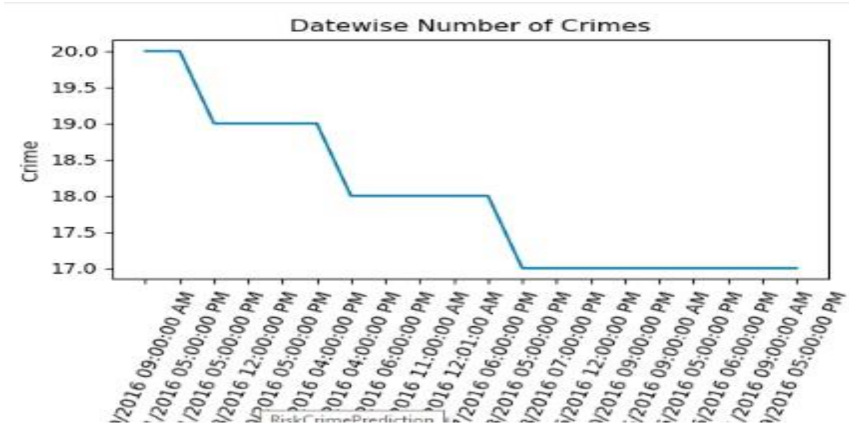

Figure 3 visualizing day wise number of crimes available in dataset

In above screen visualizing day wise number of crimes available in dataset where x-axis represents Date and y-axis represents 'Number of Crimes' on that day

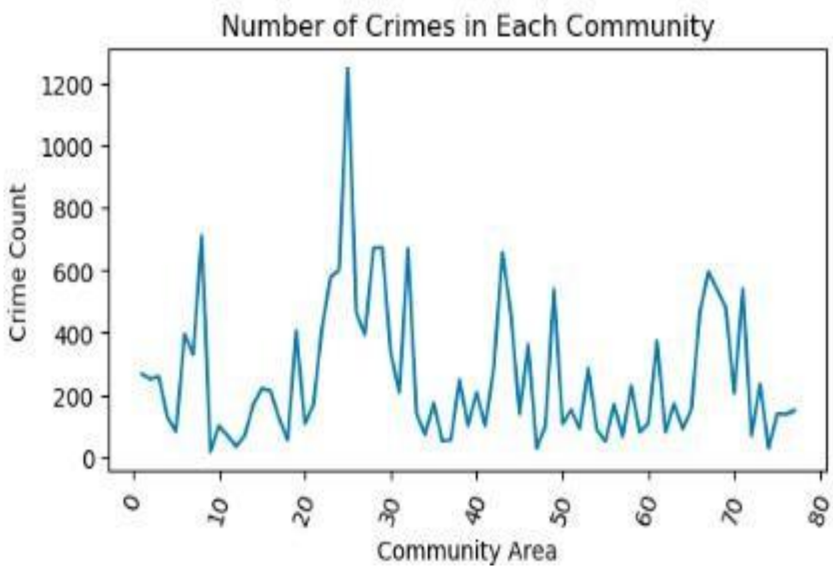

Figure 4 visualizing graph of 'Number of crimes' in different communities

In above screen visualizing graph of 'Number of crimes' in different communities where x-axis represents community ID and y-axis represents number of crimes.

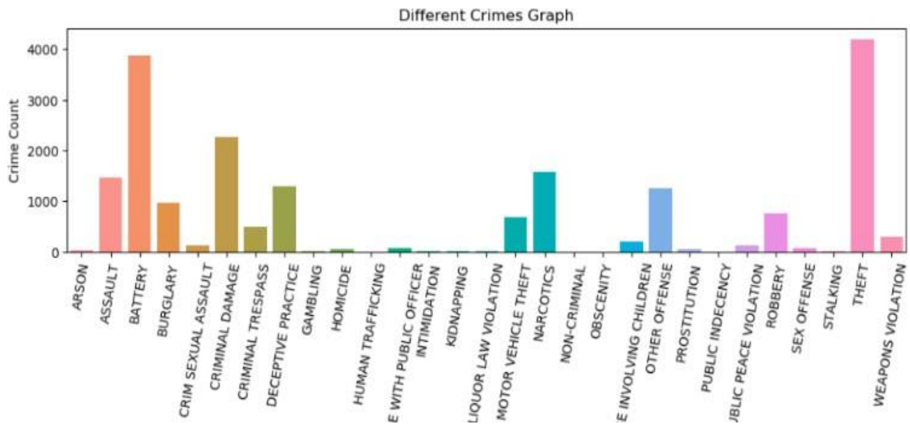

Figure 5 visualizing graph of different crimes found in dataset

In above screen visualizing graph of different crimes found in dataset where x-axis represents 'Crime Type' and y-axis represents number of crimes

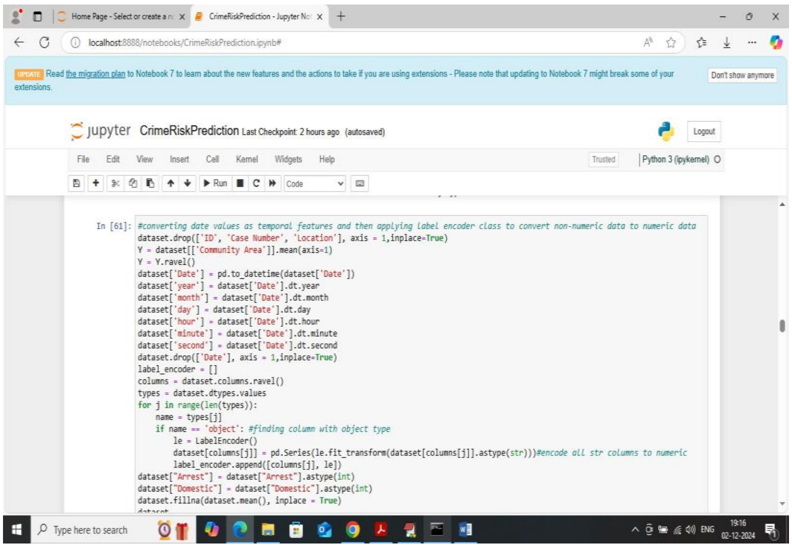

Figure 6 applying dataset processing techniques

In above screen applying dataset processing techniques such as converting date into temporal features and then applying Label Encoder class to convert non-numeric data to numeric data and then replacing all missing values with mean and after executing above block will get below output.

CONCLUSION:

In this project, we proposed, hybrid deep learning model integrating Graph CNN, Bidirectional Layer, and GRU significantly enhances crime risk prediction by optimizing feature selection and improving bidirectional learning. Unlike traditional models such as LSTM, which process data in a single direction, this approach ensures a more comprehensive analysis of crime trends, leading to higher accuracy and reliability. By utilizing real-time crime data, socioeconomic indicators, and law enforcement statistics, the system provides data-driven insights to assist law enforcement agencies in proactive crime prevention and resource allocation. The deployment of a Flask-based web interface makes it user-friendly and accessible for real-time analysis. Future work can focus on enhancing model scalability, integrating reinforcement learning, and incorporating additional crime-related factors for even more precise predictions. This research contributes to the advancement of AI-driven crime analytics, ensuring safer communities through intelligent decision-making.

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