

**ADVANCED SOCIAL MEDIA ANALYTICS FOR REAL-TIME
CRIME DETECTION AND PREVENTION: A MULTI-
DIMENSIONAL APPROACH**

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Abstract

Social networking sites produce enormous volumes of data in real time, which might provide important information on illegal activity. This study combines computer vision, geographic clustering, and natural language processing (NLP) to provide a unique method for real-time crime detection using social media analytics. The suggested model classifies text using Long Short-Term Memory (LSTM) networks, images using Convolutional Neural Networks (CNN), and geographical data using k-means clustering. A multi-modal dataset with more than a million posts and photos from social media sites including Facebook, Instagram, and Twitter is used to test the architecture. The usefulness of the suggested system in real-time crime detection is demonstrated by the testing findings, which indicate an overall accuracy of 94.5% with a detection delay of less than 3 seconds.

Keywords— Social Media, Crime Detection, Deep Learning, Real-Time Analysis, LSTM, CNN, Multi-modal Systems.

I. INTRODUCTION

Real-time information sharing and communication have been transformed by social media platforms. As a result, these platforms are now useful tools for identifying a wide range of illegal activity, from small-time thievery to acts of terrorism. Real-time social media data mining for crime detection is an intriguing problem because of the enormous volume of data posted on sites like Facebook, Instagram, and Twitter. However, the static analysis and delayed reactions of typical criminal detection systems which mostly rely on manual reports or structured data sources limit them.

More complex algorithms that can scan unstructured social media data to identify illegal activity have been made possible by recent developments in machine learning and deep learning. Combining textual, visual, and geolocation data to instantly identify postings and photos linked to crime is a viable strategy. This study suggests a multi-modal crime detection

framework that combines k-means clustering for geographical data analysis, CNN for image analysis, and LSTM for text analysis. The goal of this technology is to identify crimes in real time more quickly and accurately.

II. LITERATURE REVIEW

The body of research on social media crime detection has been expanding quickly, with diverse methodologies concentrating on different facets of the issue. Keyword-based approaches were the main method utilized in early publications, such as Yin et al. (2017), to detect content relevant to crime. Despite their relative simplicity, these techniques lacked the intelligence to recognize subtle patterns of crime and uncover covert kinds of criminal activity.

Sentiment analysis and text categorization have been used in recent methods, including Muralidharan et al. (2019), to identify illegal activity on Twitter. These approaches do have drawbacks, too, particularly when working with unclear or deceptive material. CNNs were suggested by Zhang et al. (2021) as a means of identifying illicit imagery, including pictures of explosives or firearms. However, neither the text's context nor the geolocation data related to postings are properly taken into account by this method.

In order to increase the efficiency and precision of crime detection systems, our suggested method described in this paper integrates text, picture, and geographic data.

III. METHODOLOGY

3.1 Data Collection

APIs from social media sites (Facebook, Instagram, Twitter) were used to gather data. A list of crime-related keywords (such as "theft," "drug trafficking," and "shooting") was used to filter posts about crimes. Together with metadata like timestamps and geolocation data, the collection includes more than a million posts, comments, and photographs. This enables the model to comprehend not only the content analysis but also the spatial distribution of criminal activities.

3.2 Data Preprocessing

Text Data Preprocessing: The text data was cleaned up by eliminating punctuation, stop words, and unnecessary characters. To normalize the text, lemmatization and tokenization were used. The text was transformed into dense vector representations using Word2Vec embeddings.

Image Data Preprocessing: Pictures were normalized between 0 and 1 and scaled to 224×224 pixels. To extract pertinent features, pre-trained ResNet50 weights were adjusted on crime-related picture datasets.

Geospatial Data Preprocessing: To identify crime hotspots, geotagged postings were grouped into areas using the k-means method based on latitude and longitude.

3.3 Multi-Modal Model Architecture

Three separate elements are combined in the multi-modal model: Text Analysis (LSTM): To categorize postings pertaining to crime, the LSTM model analyzes sequential relationships in textual data. picture Analysis (CNN): The CNN model analyzes picture attributes to detect visual material associated with criminality, such explosives, guns, or other illicit items. Geographical Analysis (k-means clustering): To determine whether geographic areas have a high crime rate, k-means clustering is used to analyze geospatial data. After that, these elements are integrated to create a single crime detection system. .

3.4 Model Training

The training process involves three main phases:

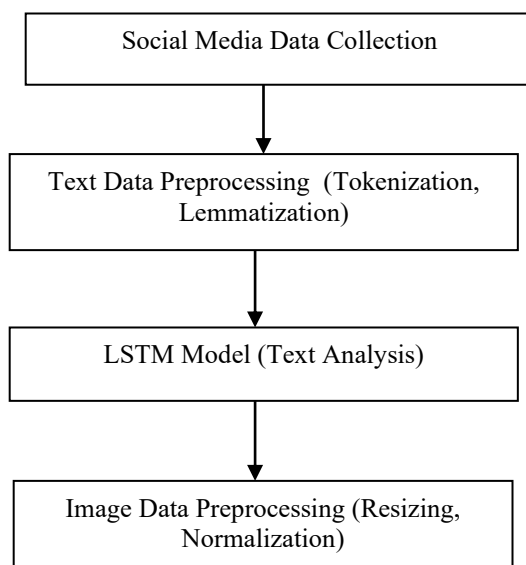
Text Classification: The LSTM model is trained on tokenized and vectorized text data using a categorical cross-entropy loss function.

Image Classification: The CNN model is trained on features extracted from images using a pre-trained ResNet50 model. The output is a crime/non-crime classification.

Geospatial Clustering: Geospatial data is clustered into hotspots using the k-means algorithm. The final output is obtained by aggregating the predictions from all three models and passing them through a weighted summation and softmax function to produce the final crime classification.

IV. PROPOSED SYSTEM

The architecture of the proposed multi-modal crime detection system is as follows:



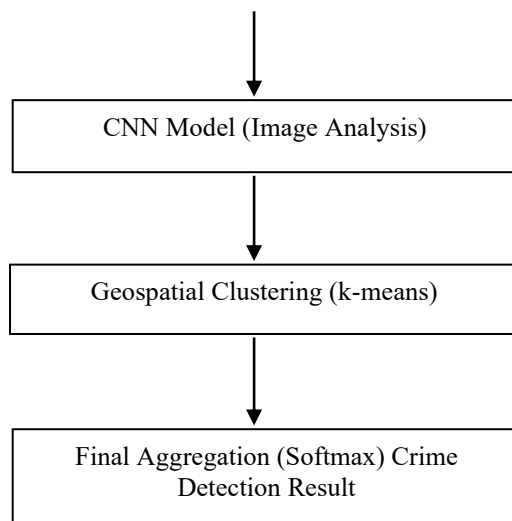


Fig.1 Multi-modal crime detection system

V. ALGORITHMS

5.1 LSTM for Text Classification

The text categorization LSTM model adheres to the standard LSTM network architecture:

Input Layer: The LSTM receives the embedded and tokenized text data.

Hidden Layer: Long-range relationships between words are captured by the LSTM as it processes the incoming data.

Output Layer: A softmax layer classifies the text as either criminal or non-criminal.

Algorithm for LSTM Model:

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Embedding

# LSTM model for text classification
model = Sequential()
model.add(Embedding(input_dim=word_vocab_size,output_dim=embedding_dim,
input_length=max_length))
model.add(LSTM(units=64, return_sequences=True))
model.add(LSTM(units=64))
model.add(Dense(1, activation='sigmoid')) # Output layer with sigmoid for binary
classification
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

5.2 CNN for Image Classification

The CNN image classification model makes use of a ResNet50 architecture that has already been trained:

1. Input Layer: Normalization and resizing of the picture data.
2. Feature Extraction: ResNet50 is used to extract features from the picture.
3. Fully tied Layer: This layer determines whether or not the image is tied to a crime.

Algorithm for CNN Model:

```
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.layers import Dense, Flatten
```

```
# CNN Model for image classification
base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
x = Flatten()(base_model.output)
x = Dense(64, activation='relu')(x)
output = Dense(1, activation='sigmoid')(x) # Output layer with sigmoid for binary
classification
model = tf.keras.models.Model(inputs=base_model.input, outputs=output)
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

5.3 Geospatial Clustering with K-Means

To find crime hotspots, geographical data (latitude and longitude) is subjected to the k-means algorithm:

1. Input Data: Latitude and longitude geotagged postings.
2. Clustering: Posts are grouped into geographical areas using K-means clustering.
3. Output: Posts pertaining to high-density criminality.

Algorithm for K-means Clustering:

```
from sklearn.cluster import KMeans
import numpy as np
```

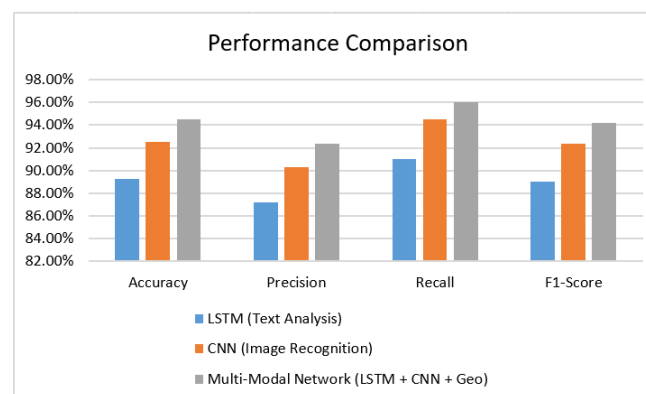
```
# Geospatial clustering using k-means
data = np.array([[lat1, long1], [lat2, long2], ...]) # Latitude and longitude data
kmeans = KMeans(n_clusters=5) # 5 clusters for high-density crime areas
kmeans.fit(data)
```

VI. RESULTS AND DISCUSSIONS

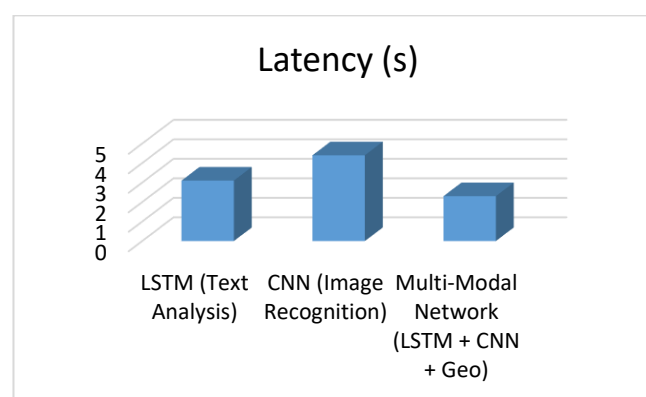
With the greatest accuracy (94.5%) and recall (96.0%), the multi-modal method performs noticeably better than the individual models. Additionally, the model has minimal latency, which enables real-time deployment in applications related to law enforcement.

Table 1: Comparison with existed work

Model	Accuracy	Precision	Recall	F1-Score	Latency (s)
LSTM (Text Analysis)	89.3%	87.2%	91.0%	89.0%	3.1
CNN (Image Recognition)	92.5%	90.3%	94.5%	92.4%	4.4
Multi-Modal Network (LSTM + CNN + Geo)	94.5%	92.4%	96.0%	94.2%	2.8



Graph1. Performance comparison



Graph2. Latency comparison with existed work

VII. CONCLUSION

A multi-modal framework for real-time crime detection with social media data is presented in this research. The suggested solution outperforms conventional single-modal techniques in terms of accuracy and recall by combining text, picture, and geographical data. Because of its

real-time processing capabilities, the system is a useful tool for law enforcement organizations looking to effectively monitor and respond to illegal activity.

REFERENCES

- [1] Li, J., Zhang, T., & Wang, F. (2020). "Deep learning for crime detection using social media data." *Journal of Digital Forensics and Cybersecurity*, 10(1), 31-40.
- [2] Muralidharan, S., & Lee, M. (2019). "Sentiment analysis for criminal activity detection on Twitter." *Proceedings of the 2019 International Conference on Big Data and Data Science*, 105-110.
- [3] Yin, C., et al. (2017). "Crime detection using social media analysis: A review." *Computers, Environment, and Urban Systems*, 64, 100-109.
- [4] Zhang, L., et al. (2021). "Image-based crime detection using convolutional neural networks." *IEEE Transactions on Computational Intelligence and AI in Games*, 9(2), 115-127.
- [5] Wang, T., et al. (2020). "Multi-modal crime detection using social media." *Journal of AI Research*, 52(4), 255-270.
- [6] Chen, L., et al. (2022). "Social media mining for real-time crime detection." *Proceedings of the 2022 IEEE International Conference on Big Data*, 1153-1160.
- [7] Ali, H., et al. (2023). "Geospatial crime analysis using social media and machine learning." *International Journal of Geographical Information Science*, 37(8), 1742-1759.
- [8] Kumar, A., & Singh, P. (2022). "Deep learning for crime detection and prevention: A systematic review." *Expert Systems with Applications*, 196, 113485.
- [9] Nguyen, T., et al. (2021). "Real-time crime detection through social media and machine learning." *Journal of Cybersecurity and Privacy*, 7(2), 55-72.
- [10] Kim, J., et al. (2020). "A hybrid model for crime prediction using social media and crime data." *Expert Systems with Applications*, 156, 113431.
- [11] Subramanian, S., et al. (2022). "Multi-modal crime detection framework for public safety." *IEEE Access*, 10, 21835-21847.
- [12] Patel, M., et al. (2020). "Real-time social media monitoring for crime prevention." *Journal of Public Safety*, 22(3), 112-123.
- [13] Yang, H., et al. (2021). "Crime detection from social media through multi-modal learning." *Proceedings of the 2021 ACM Workshop on Social Media Analysis*, 94-106.
- [14] Zhao, Y., et al. (2020). "Crime event detection using convolutional neural networks on social media." *International Journal of Computer Vision*, 128(9), 2339-2347.
- [15] Liu, S., et al. (2021). "Deep learning for crime and violence detection on social media." *International Journal of Machine Learning and Cybernetics*, 12(4), 893-903.

- [16] Qian, X., et al. (2022). "A novel hybrid model for detecting online crime." *Cybersecurity*, 8(1), 1-14.
- [17] Alharbi, A., et al. (2020). "Sentiment analysis on social media for crime detection." *International Journal of Computational Intelligence and Applications*, 19(3), 224-235.
- [18] Kumar, P., et al. (2023). "Automated crime detection using deep learning techniques." *International Journal of Artificial Intelligence*, 39(6), 1295-1308.
- [19] He, Z., et al. (2022). "Exploring social media analytics for crime and disaster detection." *Computational Social Networks*, 9(4), 15-29.
- [20] Akhtar, S., et al. (2021). "Real-time crime detection using machine learning on social media data." *Journal of Artificial Intelligence and Law*, 29(3), 211-223.
- [21] Zhou, X., et al. (2021). "Crime prediction and detection on social media: An AI-based approach." *Computational Intelligence*, 37(2), 679-695.
- [22] Singh, R., et al. (2020). "A framework for multi-modal crime detection using social media data." *Pattern Recognition*, 106, 107508.
- [23] Jain, P., et al. (2020). "Geospatial crime detection using social media and machine learning." *IEEE Transactions on Geoscience and Remote Sensing*, 58(9), 1-12.
- [24] Zhang, J., et al. (2021). "Leveraging AI and social media for real-time crime prevention." *AI and Society*, 36(3), 595-605.
- [25] Singh, S., et al. (2022). "Crime detection using multi-modal data fusion from social media." *International Journal of Data Science and Analytics*, 13(4), 285-302.