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Research article

F-LSTM: Federated learning-based LSTM framework for cryptocurrency price prediction

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Abstract: In this paper, a distributed machine-learning strategy, i.e., federated learning (FL), is used to enable the artificial intelligence (AI) model to be trained on dispersed data sources. The paper is specifically meant to forecast cryptocurrency prices, where a long short-term memory (LSTM)-based FL network is used. The proposed framework, i.e., *F-LSTM* utilizes FL, due to which different devices are trained on distributed databases that protect the user privacy. Sensitive data is protected by staying private and secure by sharing only model parameters (weights) with the central server. To assess the effectiveness of *F-LSTM*, we ran different empirical simulations. Our findings demonstrate that *F-LSTM* outperforms conventional approaches and machine learning techniques by achieving a loss minimal of 2.3×10^{-4}. Furthermore, the *F-LSTM* uses substantially less memory and roughly half the CPU compared to a solely centralized approach. In comparison to a centralized model, the *F-LSTM* requires significantly less time for training and computing. The use of both FL and LSTM networks is responsible for the higher performance of our suggested model (*F-LSTM*). In terms of data privacy and accuracy, *F-LSTM* addresses the shortcomings of conventional approaches and machine learning models, and it has the potential to transform the field of cryptocurrency price prediction.

Keywords: federated learning; LSTM; decentralization; cryptocurrencies; weight sharing

1. Introduction

The nation's economy is essential to contemporary society that impacts people's lives in numerous ways, such as employability, goods and service costs. The financial market is a crucial part of the economy, where investors purchase and sell different financial instruments, including stocks, bonds and cryptocurrencies [1]. Cryptocurrencies have become a popular investment choice for traders and investors due to their astounding volatility and the possibility of making big returns. Cryptocurrencies like Bitcoin and Ethereum have seen substantial price swings due to their decentralized nature and constrained supply, providing chances for traders to profit from market moves. Many people have been drawn to learn more about the world of cryptocurrencies as a way to diversify their investment portfolios due to the appeal of large returns in a relatively short amount of time.

The financial market has various stakeholders, including traders, investors, regulators and financial institutions. The cryptocurrency market is extremely dynamic, where market sentiments, news and events are few variables that can affect cryptocurrency's price. Since, the cryptocurrency prices are so erratic, it is difficult to predict it with some degree of certainty [2]. As a result, traders and investors frequently use methods including technical analysis, fundamental research and market trends to forecast cryptocurrency prices. However, technical analysis and market trends are the foundation of conventional methods for forecasting cryptocurrency values [3, 4]. To forecast the future trends of cryptocurrency prices, the technical analysis examines historical market data, i.e., price and volume. This strategy makes the assumption that previous market data can provide insight into potential market developments. Traditional approaches have several shortcomings that reduce their accuracy, and for instance, technical analysis does not take into consideration fundamental variables like news, events and market sentiment that can impact cryptocurrency prices [5]. Similarly, market patterns can unexpectedly shift, making predicting prices difficult. Thus, conventional approaches could not yield accurate predictions, particularly in extremely volatile markets like the one for cryptocurrency.

Machine learning techniques can be used to increase the precision of price predictions for cryptocurrencies [6–9]. Machine learning models analyze the historical market data (price and volume) to forecast future trends and identify intricate data patterns that conventional approaches could miss. Machine learning models do, however, have several drawbacks, such as overfitting and data bias. The accuracy of predictions may be impacted by these restrictions, particularly if the training data is sparse or biased. Deep learning techniques, particularly the LSTM model, have demonstrated promise in predicting cryptocurrencies' prices to overcome them [10, 11]. Traditional machine learning models might be unable to capture the temporal dependencies in the data that the LSTM model can do. LSTM model can also handle the high-dimensional, non-linear data that characterizes financial markets. However, since LSTM models need a lot of training data, centralized systems might not have it.

The aforementioned issues can be resolved using federated learning. It is also a remedy for the issue of data privacy in centralized systems. Model training on decentralized data sources is made possible using FL without compromising the data privacy [12]. In this, the model is trained using local data sources, and only the model parameters (weights) (not the raw data) are shared. In order to increase accuracy while maintaining data privacy, we present a federated learning-based LSTM model for cryptocurrency price prediction in this study. The suggested approach addresses the shortcomings of conventional and machine learning techniques while utilizing the benefits of LSTM models. With the LSTM models being trained locally on remote devices with incremental projections of data over time, the models increase the accuracy and precision in local devices, and through the utilization of a FL framework, the global model adapts to the incrementally learned weights. The proposed framework provides a solution to higher optimization and privacy preservation. The modular framework overall thus achieves a significant decrease in loss with time using simple *FedAvg*, making the system efficient, optimized, privacy preserved and secured. The loss after global iterative training is at the minimum of 2.3×10^{-4} without any data transfer to a centralized server. Furthermore, the proposed model operates at an exceptionally low memory and CPU cost and gives highly accurate predictions.

1.1. Research contributions

The following are the contributions of this paper.

- We proposed a unique Federated Learning-based LSTM model for cryptocurrency price prediction that improves prediction accuracy and gives an almost negligible loss compared to traditional and machine learning methods.
- A significant outcome of this paper on FL is the ability to train models on decentralized data sources without compromising data privacy. The central server receives no raw data from the proposed model, only its model parameters (weights). Increased model openness, accountability and audibility are also made possible by the decentralized approach.
- Another significant contribution is that the suggested model can be expanded while retaining a high level of accuracy to accommodate a large number of participants. The model may be trained on many devices at once thanks to federated learning, which enables model training on decentralized data sources. This strategy can shorten the training period, increase the model's accuracy and diversify the training data.
- The Proposed framework Federated Integrated LSTM model *F-LSTM* presents a highly efficient system for forecasting prices without actually training on the original set of sequential data. The Framework works in a dynamic environment for both discrete and sequential data forms. Through the realization of the incremental learning technique, the model works in real-time for continuously evolving data with a constant and steady loss of 2.3×10^{-4}.

1.2. Organization

The arrangement of the paper is as follows. Section 2 defines the novelty in our proposed framework. The relevant works in the area of price prediction are described in Section 3. Section 4 comprises the system Model and problem formulation for the same. The proposed *F-LSTM* framework for cryptocurrency price predictions is presented in Section 5. The focus of Section 6 is on the outcome and analysis of the suggested framework. The paper is concluded in Section 7.

2. Novelty

In this study, we present a novel sequential framework that deviates from the usual predictive abilities connected with conventional LSTM models. We are not primarily concerned with making predictions as is done in the past as presented in [13] and [14]. Instead, we suggest a novel strategy designed to give consumers a computationally effective substitute as described in [12], particularly for local device training. Our system is specifically made to drastically cut down on overall computing costs, outperforming current state-of-the-art models in this regard.

Our framework's ability to strike a careful balance between maintaining the predictive power of individual models and streamlining the training of a global model is one of its fundamental advances. Notably, this optimization is accomplished without requiring repeated data access. In summary, while we effectively adjust the weights of the global model, our architecture ensures that the predictions made by individual models remain intact. This is done without having to access often and manipulate huge amounts of data or keep up a centralized data repository.

The proposed framework is meticulously built to comply with the highest optimization requirements, producing a worldwide model with remarkable precision as a result. Our method is unique because it can do rid with the necessity for centralized data storage and comprehensive data access. With the help of this special feature, distributed sequential learning will be able to explore new and intriguing directions without having to make significant structural changes.

3. State-of-the-art works

This section discusses the related work carried out by researchers in the field of stock and cryptocurrency price prediction. Numerous studies have explored different methodologies and approaches to forecast prices, aiming to provide valuable insights for decision-making, risk management and investment strategies. Traditional price prediction methods use machine learning and deep learning methodologies to predict prices based on historical data. For instance, reference [15] presented a transformer-based attention mechanism for stock price prediction. The attention mechanism helps the model to focus on the most significant portions of the input sequence when generating the output sequence. This results in the extraction of the most important features. However, training such a framework requires huge computational resources and high training time.

Further, references [16] and [17] depicted frameworks developed on hybrid models, combining multiple machine and deep learning techniques. The authors in [16] proposed a FinBERT-LSTM deep learning-based stock price prediction model with news sentiment analysis. It gives an accuracy of 0.9859 for the NASDAQ-100 index stock while giving a remarkably low mean absolute percentage error of 0.014. However, this framework is overly dependent on the quality of the FinBERT model and requires extensive parameter tuning for optimal results on varied datasets. On the other hand, reference [17] proposed a hybrid model that encapsulates attention-based convolutional neural network (CNN)-LSTM and XGBoost for stock price prediction. The hybrid nature of the model improved robustness and generalizability. However, the working of their framework requires high computing power, and the combination of the attention mechanism and XGBoost restricts the interpretability of the framework to a certain extent.

Later, reference [12] presented a federated learning-enabled predictive analysis model to forecast stock market trends. Federated learning-based random forest and support vector machine (SVM) models are used in its development. Random forest gave a minimum squared error of 0.021, while the SVM model, when deployed, gave a minimum squared error of 37.596. FL permits privacy-preserving and distributed learning. This led to its ability to leverage diverse data sources. However, using random forest and SVM leads to limited accuracy and a high error score. Better algorithms like LSTM or Bi-directional LSTM can boost the prediction accuracy and minimize the loss. The authors of [18] presented a Bi-LSTM network to predict the price of Bitcoin. It is a recurrent neural network consisting of two LSTM layers processing the input sequence in both forward and backward directions to capture long-term dependencies in sequential data. The Bi-LSTM Network captures dependencies in both forward and backward directions, resulting in a good RMSE. However, it is likely to suffer from overfitting and cannot handle anomalies in the market [19].

Furthermore, reference [20] proposed an integrated approach using hybrid LSTM-ELM for Bitcoin price forecasting. LSTM and ELM algorithms are combined to create a hybrid LSTM-ELM model (Long Short-Term Memory - Extreme Learning Machine) to increase the precision of time-series predictions. The model's LSTM layer captures the temporal dependencies in the input sequence, and the ELM layer is employed as a quick and effective way to train the network's output layer. This results in high accuracy (0.9397 and 0.9469 in two low volatility periods and 0.9328, 0.9004 and 0.9525 in three high volatility periods), along with minimal error due to the high effectiveness of the hybrid model. However, this model is likely to suffer from overfitting due to its complexity and requires a large amount of historical data to be trained effectively. After this, reference [21] presented a CNN-LSTM Model for cryptocurrency price forecasting. The dual algorithm nature of this model allows it to capture both short-term and long-term dependencies in the input data to maintain high accuracy and precision. Another advantage of this model is that it can handle sequential and non-sequential data. Additionally, the framework has been evaluated on a variety of evaluation metrics. However, it proves to be very computationally expensive, and the effectiveness of predictions may differ for varying cryptocurrencies. Finally, reference [22] gives an LSTM-based Bitcoin price prediction framework. An optimized LSTM is used, which gives a phenomenally low error of 288.5989. Another merit of using LSTM is that it can learn to forget or retain information selectively. However, the naïve LSTM model is not generalizable for other cryptocurrencies and improved accuracy and lower error can be achieved if combined with other techniques.

There are some methods that can be used to predict stock market prices, which are described by [13]. This study of deep learning frameworks concisely describes several deep learning frameworks that can be used to predict stock market trends. Some of them are Large language models (LLM), Time series forecasting, deep neural networks and feature engineering for identifying relevant features. Reference [14] reviews a wide variety of machine learning and deep learning techniques for predicting the stock market prices by utilizing the power of fundamental indicators such as PE ratio and moving averages, which are effective in the long run but come with the factor of uncertainty to forecast the price action with minimum loss.

In the relevant works mentioned above, different methods for price prediction employing machine learning techniques were highlighted. However, these methods have inherent drawbacks and are frequently insufficient for various reasons, including high computational demands, a lack of privacy and centralization difficulties. We provide an LSTM-based decentralized, federated learning strategy that eliminates several drawbacks. Our suggested model uses fewer computational resources and achieves a smaller loss in time-series prediction tasks, making it a more effective and privacy-preserving option. Overall, our suggested model overcomes many of the shortcomings of previous approaches and provides a promising solution for time-series prediction applications. Table 1 displays the relative comparison between the state-of-the-art works and the proposed work.

Table 1. Comparative analysis of the proposed framework with the existing state-of-the-art schemes for cryptocurrency price prediction.

Authors	Year	Description	Algorithms Used	Merits	Demerits
Ardakani et al. [12]	2023	Uses SVM as a base model for identifying and recognizing patterns while integrating the base model with federated learning for decentralizing the learning model	SVM integrated with Federated Learning	Enables privacy-preserving; can leverage diverse data sources	Poor accuracy/loss
Jiang et al. [13]	2021	Presents several state-of-the-art models and frameworks that are proficient and widely used in forecasting sequences and prices.	ARIMA, LLM, GARCH	Develops a concise understanding of the approaches that can be used in a synergistic way to predict market prices	The study of the models is clear, but use in a combined manner is not explained
An et al. [14]	2022	Proposes various machine learning and deep learning procedures to predict stock market price actions.	Regression, Classification	A concise approach for versatile use of algorithms	No detailed description of models
Zhang et al. [15]	2022	Transformers used for learning the sequences of the prices in the financial market data and accurately regenerate the useful features and patterns in the sequences.	Transformer Encoder-based Attention Network (TEANet) framework	Effective feature capturing	Computationally expensive; high training time
Halder [16]	2022	Deep LSTM model integrated with pretrained language model with the add-on of sentiment analysis for reducing the randomness and capable of capturing nuanced languages and context specifications.	FinBERT-LSTM	Good accuracy (0.9859); two technologies	Overly dependence on FinBERT; extensive parameter tuning
Shi et al. [17]	2021	Combines CNN-LSTM and XGBoost by catching important portions of time series data using an attention-based mechanism by integrating a hybrid approach of CNN learning and sequence learning patterns.	CNN-LSTM and XGBoost hybrid model	Robust; generalizable; able to incorporate multiple sources of data	Computationally expensive; limited model interpretability
Nithyakani et al. [18]	2021	Uses Bi-LSTM model to capture both past and future dependencies in the sequential data for predicting the prices if Bitcoin	Bi-LSTM	Captures dependencies in both forward and backward directions(past and future)	Overfitting; flawed anomaly handling
Luo et al. [20]	2022	Integrates LSTM with ELM machine learning models for predictions and forecasting of input sequences where the ELM algorithms enhance the predictions made by LSTM	Hybrid LSTM-ELM	high accuracy (0.9512); effective model	Overfitting; requires a large amount of data for effective training
Livieris et al. [21]	2021	Uses image representation of historical prices of cryptocurrency for forecasting future prices by integrating CNN with LSTM using a sliding window approach by utilizing both spatial and temporal features	CNN and LSTM	minimal error (MAE is 0.005 and RMSE is 0.007) & Precision; handles both sequential and non-sequential data	Computationally expensive; tentative overfitting
Ferdiansyah et al. [22]	2019	Uses normal LSTM model for forecasting the Bitcoin prices on the sequential data of Yahoo Finance	LSTM	Very low error (RMSE is 288.59); can selectively forget or retain information	Generalizability issues
Proposed framework	2023	*F-LSTM*: Federated Learning-based LSTM Framework integrated with Incremental learning on the sequential data for cryptocurrency price prediction	Federated Learning-based LSTM framework	high precision; minimal error(MSE is 0.0002); decentralization; enhanced privacy and security; high generalizability of model	-

4. System model and problem formulation

This section presents the system model and problem formulation for the proposed *F-LSTM* model. In the everlasting global economy of randomness and rapid changes, the most variably-correlated factor for forecasting the trends of the current economy is the stock market trends. These trends efficiently describe the economic situation of a country or a group of organizations by weighted aggregation of independent factors regressed together. Many fellow researchers made great attempts to forecast the trends of stock markets and have been successful to attain the closest accuracy possible through the use of a heavily trained transformers model. This accuracy is attained at a heavy cost of the vast utilization of computational resources embedded together for the training over the large dataset. The proposed architecture aims to present an optimized solution by solving both the optimization and scalability problems of the previously trained models. In the proposed system, the client-server is established as individual devices $\{C_1, ..., C_i, ..., C_j, ..., C_m\} \in C$ where the client is referred to as a diversified entity which can be described as an individual or an organization with individual data consisting of respective stock market fluctuations upon a myriad number of stocks. The set $\{T_1, ..., T_i, ..., T_j, ..., T_m\} \in T$ represents the trends or fluctuations in the value of these stocks. These trends are monitored by LSTM models, $\{L_1, ..., L_i, ..., L_j, ..., L_m\} \in L$, which are deployed by different investors or financial institutions.

Equations (4.1) and (4.2) represent a stock that can exhibit one or more trends.

$$\exists C_i \in C \xrightarrow{has} T_i \in T \Leftrightarrow C_i, T_i \tag{4.1}$$

$$\exists C_i \xrightarrow{has} T_2, T_3, ..., T_j \in T \tag{4.2}$$

In Eqs (4.3) and (4.4), if a cryptocurrency exhibits a trend, it is categorized as an "active cryptocurrency"; otherwise, it is a "dormant cryptocurrency".

$$C_i \cap T_i \neq \emptyset \rightarrow ActiveClient \tag{4.3}$$

$$C_i \cap T_i = \emptyset \rightarrow DormantClient \tag{4.4}$$

Upon successful categorization of a cryptocurrency trend's occurrence on a client-server, respective clients are characterized as active or dormant. The LSTM model learns from the historical data and makes forecasts upon the training from the input stock data, and the global FL model identifies the active client weights and dormant client weights upon applying the *Federated Averaging* algorithm to each client server transition.

The system uses FL to solve the problem of scalability. With federated learning, each LSTM model at the edge node (investor or financial institution) is trained on its local data. The models then send their learnings (model's updated weights) to a central server, where they are aggregated to form a global model weight. These global model weights are then sent back to the edge nodes to reset the individually trained weights of the nodes, and the process iteratively optimizes the proposed approach. Furthermore, this approach allows for training on a much larger dataset than what a single LSTM model could handle, leading to more accurate and robust predictions.

The optimization problem is addressed by tuning the LSTM models and the FL process to maximize the accuracy of the predictions while minimizing the computational and communication costs. This involves optimizing the number of layers in the LSTM models, the number of iterations in the FL process and the updated model weights.

5. The proposed framework

This section describes the proposed system model architecture Ψ (as shown in Figure 1) for forecasting the prices of a particular cryptocurrency, Ethereum, upon training on the determined span of years. The framework is divided into 3 distinct layers, i.e., data, AI and application layers. The functionality of each layer is described as follows.

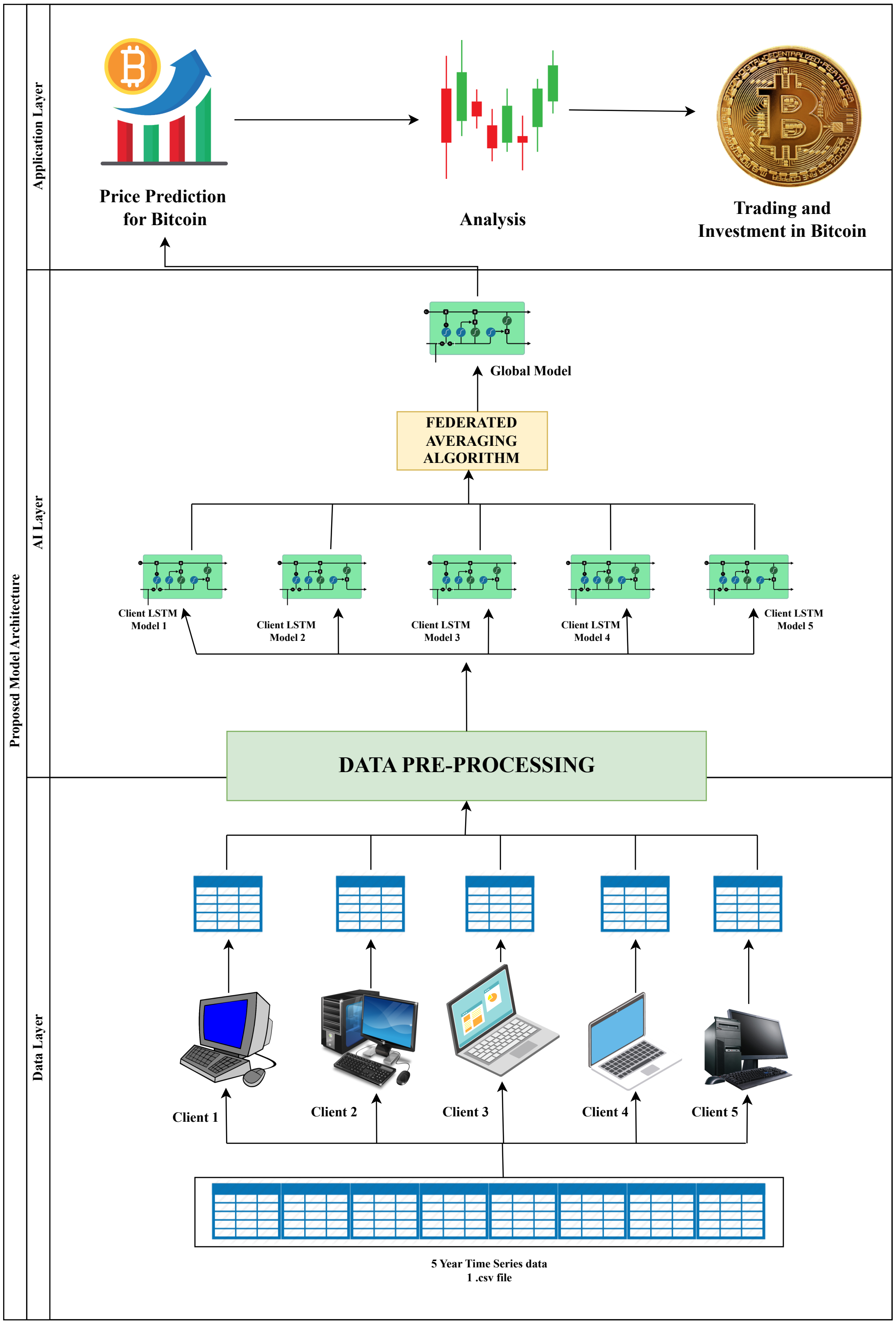


Figure 1. System architecture.

5.1. Data layer

The data layer includes several financial markets $\{M_1, ..., M_i, ..., M_j, ..., M_m\} \in M$ that can be used to track market activity and record stock price fluctuations. These markets distribute real-time stock prices, which the suggested framework (LSTM model) then uses to forecast the future occurrences of trends. From the price data, it is to determine whether any significant price movement for the stocks $\{S_1, ..., S_i, ..., S_j, ..., S_m\} \in S$ will occur and classify them as bullish (price likely to rise) or bearish (price likely to fall). This is determined by whether or not the stock exhibits any specific trend $\{T_1, ..., T_i, ..., T_j, ..., T_m\} \in T$ in the price data. The data is captured in the form of a time series and is further forwarded to the AI layer, which makes overall predictions. This is done through the FL process, where the LSTM model is trained across multiple decentralized edge devices, each corresponding to a particular financial market. The model learns from the local data on each device, and the global model is updated by aggregating these local updates by the data available on the local devices.

5.2. Artificial intelligence layer

The AI layer consists of multiple LSTM models $\{L_1, ..., L_i, ..., L_j, ..., L_m\} \in L$, each corresponding to a specific financial market within the set $\{M_1, ..., M_i, ..., M_j, ..., M_m\} \in M$. These LSTM models are utilized to predict stock price trends and movements for each stock $\{S_1, ..., S_i, ..., S_j, ..., S_m\} \in S$ in the respective financial market. The stocks are distributed among the set of clients $\{C_1, ..., C_i, ..., C_j, ..., C_m\} \in C$. Each client has LSTM models $L_i \in L$ integrated within the system. These models are trained on a particular stock $S_i \in S$ tuned to identify the trend $T_i \in T$ in the data. Further the respective weights $\{W_1, ..., W_i, ..., W_j, ..., W_m\} \in W$ of each model are sent to the global server for aggregation and sent back to a cluster of distributed clients. In a bullish trend, the stock price is expected to rise, while in a bearish trend, it is expected to fall. Equations (5.1) and (5.2) represent the LSTM model's capability to classify a stock's trend based on the time-series data.

$$LSTM(L_i) \rightarrow S_i \cap T_i \neq \emptyset \rightarrow Bullish \tag{5.1}$$

$$LSTM(L_i) \rightarrow S_i \cap T_i = \emptyset \rightarrow Bearish \tag{5.2}$$

The LSTM models are trained using federated learning. The learning process takes place across a cluster of decentralized edge devices, each corresponding to a specific financial market. Each LSTM model learns from the local time-series data, after which the weight updates are aggregated to form the global model weights. These global model weights are then sent back to the local LSTM cluster edges, leading to an improved second round of learning. This process continues in iterative cycles, leading to progressively more accurate predictions over time. The AI Layer thus not only performs the predictive analysis but also ensures the preservation of privacy along with scaling the model over distributed systems and optimizing the performance throughout each iteration by the use of FL systems. The FL approach enables the AI layer to handle large-scale data from multiple financial markets without the need for centralization, making it a powerful tool for predicting stock market trends.

5.2.1. Dataset description

The dataset used to train the *F-LSTM* model is obtained from the *Yahoo Finance API*, which provides large-scale historical data of many organizations and global market trends [23]. It conventionally comprises of 7 attributes $Open$, $High$, Low, $Close$, $Volume$, $Dividend$, $Stock\ Split$. The time frame length taken is 1825 time series points for model training. In the proposed system, numerous trends and fluctuations occur over a period of time $\{T_1, ..., T_i, ..., T_j, ..., T_m\} \in T$ and these trends are recognized by the formulated model.

5.2.2. Dataset preprocessing

First, we store the multivariate time-series data δ in cloud storage and subsequently load it for preprocessing to enhance training accuracy and prediction outcomes. Initially, the data is normalized to a standard range, typically between 0 and 1, to manage outliers and ensure the model can handle extreme values effectively. The mathematical representation of normalization is described as follows.

$$\delta \rightarrow (x, y) \rightarrow (\frac{x}{x_{max}}, y) \tag{5.3}$$

Equation (5.3) represents the mapping and scaling of data, where x is the variable used to denote the tensors comprising values of the multivariate time-series data, and y is the variable used to denote the label or target variable. The data is configured in a way such that a multivariate base LSTM model can be designed to make accurate and precise predictions. This is done by parsing the data comprising attributes $Open$, $High$, Low, $Close$ and $Volume$ into a multi-dimensional $Numpy$ array with all the respective attributes taken into consideration.

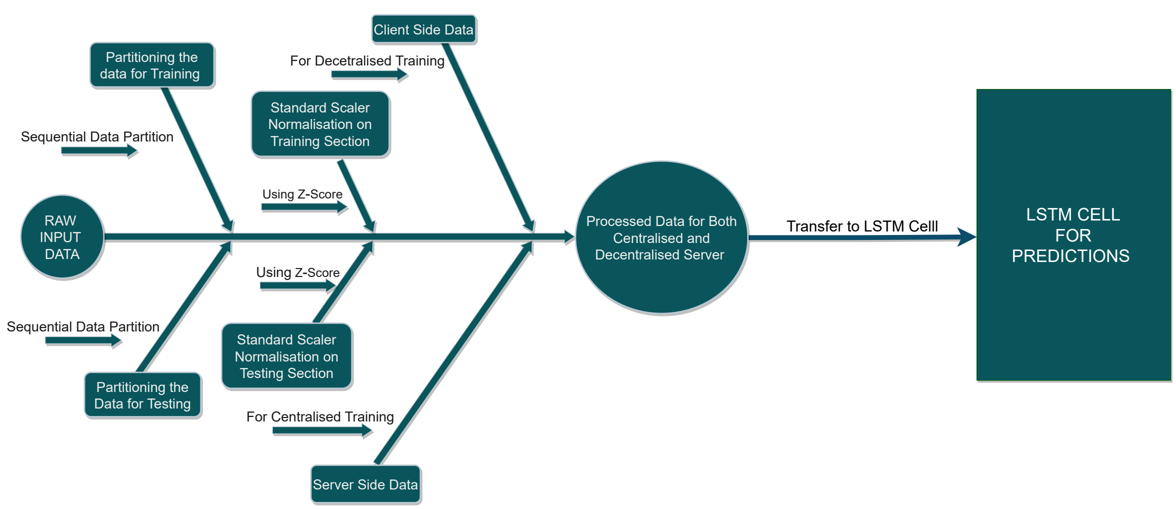


Figure 2. Data preprocessing.

The $Numpy$ array is then scaled and normalized for better performance and optimized computation while training. The scaled data is divided into a training set (80% of the data) and a test set (20% of the data). It is also ensured that the test data includes a certain number of previous time steps (defined by sequence length, set to 50) before the start of the test period. In the proposed model, FL is integrated, which means that each LSTM model learns from its local batch of data. After local training, the models' updates are sent to a central server where aggregation for computing the global weights is performed. These calculated global weights are then sent back to each local LSTM model, enhancing the subsequent learning cycle. This iterative process progressively refines the model's predictions over successive cycles. The entire flow of data preprocessing is shown in Figure 2.

5.2.3. Model motivation

The inability of conventional and machine learning methods to effectively predict the extremely volatile and non-linear cryptocurrency market is the primary motivation behind the development of a *F-LSTM* model for price prediction. The traditional approaches are based on historical data and stationary state assumptions, which are not always valid in the complicated and volatile cryptocurrency market. Similarly, because machine learning models are trained using centralized data sources that might not accurately reflect the variety of the market, they are susceptible to bias and overfitting. Furthermore, privacy issues are a crucial problem when predicting cryptocurrency prices because centralized data sources may put sensitive information at risk. Therefore, a decentralized and safe method of cryptocurrency price prediction is required, one that guarantees high accuracy while protecting the privacy of sensitive data. Furthermore, privacy issues are a crucial problem when predicting cryptocurrency prices because centralized data sources may put sensitive information at risk. Therefore, a decentralized and safe method of cryptocurrency price prediction is required, one that guarantees high accuracy while protecting the privacy of sensitive data.

These issues are resolved by *F-LSTM* framework, which enables the historical pattern learning algorithm in a multimodal environment. The algorithms are made intact to adapt with increments of data shards into the local client repository and learn over time. The framework thus identifies the effective sequential patterns in the data and combines local models' individual understanding to tune and optimize the global model. The global model thus learns better than individual clusters and generates an optimized solution. This solution as a whole is considered to be the versatile answer for application-based software who are destined to learn on a large chunk of data and have to evolve on the newly available data continually. Thus, considering all the constraints for satisfying evolutionary incremental learning along with preservation of the individual data characteristic *F-LSTM* framework, proves to be an efficient approach for building optimized software.

Furthermore, we analyzed [24], which was a study that used a model based on long short-term memory to forecast energy consumption in order to improve prediction performance, and [14], where an empirical study was done on two cases of pork prices and soybean futures prices, and 12 comparative prediction models were developed based on random forest (RF), LSTM and multilayer perceptron (MLP). These studies demonstrated the strengths of LSTM for price prediction and hence, we were motivated to develop the proposed framework on the LSTM algorithm due to the several reasons that are stated below.

- **Capturing long-term dependencies**: The purpose of LSTM networks is to identify long-distance dependencies in sequential data. The capacity of LSTM to capture long-term patterns is vital in cryptocurrency markets, as prices are affected by previous patterns and occurrences.
- **Handling temporal dynamics**: Prices for cryptocurrencies display complex temporal dynamics, including seasonality and volatile swings. Since LSTM is so efficient at modeling and adjusting to such temporal fluctuations, it is appropriate for situations found in dynamic markets.

- **Memory cell**: A dedicated memory cell in the LSTM can store and spread data over a long period of time. For the purpose of recalling historical pricing trends and putting them into forecasts, this feature is crucial.
- **Sequence-to-sequence learning**: Sequence-to-sequence learning is supported by LSTM, enabling it to forecast future sequences using existing price sequences as input. This is crucial for forecasting full price trajectories rather than just specific price points.
- **Robust to noisy data**: Cryptocurrency data can have outliers and sharp spikes, making it noisy. LSTM can learn to weed out irrelevant data and concentrate on the underlying patterns while being robust to noisy input.
- **Adaptability**: LSTM models are flexible and rapidly respond to shifting market circumstances. In the rapidly changing and highly volatile world of cryptocurrency, adaptation is essential.

5.2.4. Model development

The proposed *F-LSTM* model ψ is built upon a sequence-to-sequence architecture (as shown in Figure 3), with the input tensor's size determined by the training data's shape which is described in Eq (5.4).

$$n_{\text{neurons}} = x_{\text{train}.shape[1]} \times x_{\text{train}.shape[2]}. \tag{5.4}$$

The initial tensor, of size calculated from the Eq (5.4), is first passed through the LSTM block with n_{neurons} neurons, where n_{neurons} is the product of the second and third dimensions of the training data. The second dimension denotes the number of data points in the training sample, and the third dimension denotes the number of independent variables considered for the training of the ψ model.

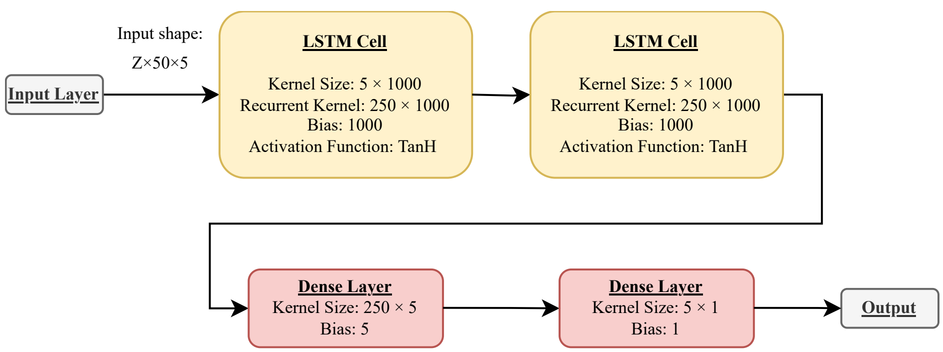


Figure 3. LSTM model architecture.

Each LSTM unit computes the current cell state c_t and the current hidden state h_t as follows:
1) *Forget gate* (f_t): Determines what information the cell state should forget.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5.5}$$

2) *Input gate* (i_t): Determines what new information the cell state should store.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5.6}$$

3) *Cell state ($\tilde{C}_t$)*: A candidate value for the cell state.

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{5.7}$$

4) *Update of the cell state (c_t)*: Update the old cell state c_{t-1} into the new cell state c_t.

$$c_t = f_t * c_{t-1} + i_t * \tilde{C}_t \tag{5.8}$$

5) *Output gate (o_t)*: Determines what the next hidden state should be.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5.9}$$

6) *Update of the hidden state (h_t)*: Update the old hidden state h_{t-1} into the new hidden state h_t.

$$h_t = o_t * \tanh(c_t) \tag{5.10}$$

Here, σ denotes the sigmoid function, and $*$ denotes element-wise multiplication. The weight matrices W_f, W_i, W_C and W_o, and the bias vectors b_f, b_i, b_C and b_o are iteratively updated and are relaxed to learn throughout the training of the model as an overall. In a neural network, a dense layer represents a matrix-vector multiplication. The values in the matrix are the trainable parameters (weights) that get updated during backpropagation. A conventional neural network layer l is denoted as follows.

- $x^{[l]}$ as the input to layer l
- $W^{[l]}$ as the weights of layer l
- $b^{[l]}$ as the bias of layer l
- $g^{[l]}$ as the activation function of layer l

The output after computation of the respective layer l is shown in Eq (5.11)

$$z^{[l]} = W^{[l]} \cdot x^{[l]} + b^{[l]} \tag{5.11}$$
$$h^{[l]} = g^{[l]}(z^{[l]}) \tag{5.12}$$

Following the LSTM layers, the model introduces a fully connected (Dense) layer with five neurons. This dense layer performs the weighted computation of inputs attained from the output of the previous LSTM layers. The model culminates in an output Dense layer with a single neuron. The output of this neuron is the prediction of the model. The model overall is a regression model to forecast the single next value in the sequence of the time series.

The model structure is defined, and at the later stages, it is compiled with the Adam optimizer and the evaluation metrics, i.e., the Mean Squared Error (MSE) as the loss function. The Adam optimizer is an extension to stochastic gradient descent that adapts learning rates for each weight in the model, improving the classic stochastic gradient descent. The MSE loss function is considered to be the most appropriate for regression problems and measures the average of the squares of the errors, i.e., the average squared difference between the estimated values and the actual value. To further enhance privacy preservation and data efficiency, the tuned LSTM model is augmented with an FL approach. Instead of the traditional way where data is sent to a centralized location, the FL approach allows for the model training to happen on the client devices themselves, therefore keeping the data local.

This approach is highly beneficial in scenarios where the data is sensitive or massive, which makes it challenging to centralize, and a crucial factor of privacy preservation is in need. The integration of FL with the LSTM model follows specific steps.

1) *Initialization* - A global LSTM model is initialized on the server, and its weights are shared with all the client devices.

2) *Local Training* - Each client device trains the received model on its local data. This training includes the forward pass, backward pass and weight updates, which are all performed locally.

3) *Model Aggregation* - After local training, each client sends their model updates (i.e., the changes in weights and biases) to the server. Importantly, the raw data never leaves the client's device, maintaining data privacy.

4) *Global Update* - The server aggregates the received updates from all clients and updates the global model. The aggregation can be a simple averaging or a more sophisticated method depending on the use case. The updated global model is then shared with all the clients, and the process repeats.

The crucial part of FL is the aggregation of the model updates on the server. The most common aggregation method is Federated Averaging (FedAvg), which is simply the weighted average of the model updates from all clients. Given K clients, where each client k has a weight update ΔW_k and a bias update Δb_k, the global weight and bias update ΔW and Δb can be calculated as follows.

$$\Delta W = \frac{1}{K} \sum_{k=1}^{K} \Delta W_k \tag{5.13}$$

$$\Delta b = \frac{1}{K} \sum_{k=1}^{K} \Delta b_k \tag{5.14}$$

The global model parameters (weights) are then updated using these averaged updates.

$$W = W + \Delta W \tag{5.15}$$

$$b = b + \Delta b \tag{5.16}$$

The notable factor while performing the computation in a real-time environment is the averaging can be weighted based on the number of samples each client has. Clients with more data would contribute more to the global model update. The FL process, including Federated Averaging, is done iteratively over multiple rounds until the model performance converges. This ensures that the model learns from the entire distributed data while keeping the data local to each client. The integration of FL into the LSTM model allows for efficient learning from distributed data sources while respecting the privacy of the data owners. The model training can be seen as a cooperative effort, where each client contributes to the learning process, thus enabling the model to learn from a more diverse and representative dataset.

The procedure is repeated iteratively over time to attain minimum loss from the predictions as described in the Algorithm 1.

Algorithm 1 FL-LSTM (FL with LSTM)

procedure FL-LSTM (W, b)
  Preprocess the input data using a standard scaler method
  Let X be the input data
  Compute the mean for each feature:
    $\mu = \frac{1}{N} \sum_{i=1}^{N} X_i$
  Compute the standard deviation for each feature:
    $\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (X_i - \mu)^2}$
  Scale the input data:
    $X_{\text{scaled}} = \frac{X-\mu}{\sigma}$
  Initialize the LSTM model with multiple LSTM layers:
    model = Sequential ()
    model.add (LSTM (units, return_sequences = True))
    . . .
    model.add (LSTM (units, return_sequences = False))
    model.add (Dense (output_size))
  for each round r **do**
    Select K clients at random
    for each client k in K **do**
      Initialize $W_k, b_k \leftarrow W, b$
      Compute $\Delta W_k, \Delta b_k$ from client's preprocessed data using LSTM
      Send $\Delta W_k, \Delta b_k$ to server
    end for
    Server updates W, b as $W \leftarrow W - \sum_k \Delta W_k$, $b \leftarrow b - \sum_k \Delta b_k$
  end for
end procedure

5.3. Application layer

To provide real-time price predictions for the cryptocurrency, Ethereum, the application layer of the system architecture for the *F-LSTM* model, is essential. The model gets continuous data streams from various sources, such as exchange APIs and market data providers, at this layer, assuring the availability of up-to-date information. The LSTM model, trained using FL strategies, makes use of the combined intelligence of numerous participants while preserving the security and privacy of the data. The algorithm dynamically changes its forecasts as fresh pricing data comes in, allowing users to make wise trading and investment decisions. Once the price predictions are generated in real-time, the application layer facilitates further data analysis. This analysis can involve various techniques such as statistical analysis, pattern recognition and anomaly detection to extract meaningful insights and identify potential market trends. Traders and investors can utilize these insights to understand the market dynamics, evaluate risk factors and make informed decisions regarding their cryptocurrency portfolios. By integrating the LSTM model with the analysis capabilities at the application layer, users gain a comprehensive understanding of the cryptocurrency market, enabling them to optimize their trading strategies and potentially maximize their returns on investments in cryptocurrencies.

6. Results and discussions

In this section, we discuss the performance analysis of the proposed framework using different evaluation metrics, such as training loss, validation loss, resource utilization and computation time. A detailed result analysis is as follows.

6.1. Experimental setup and simulation parameters

The work on the proposed framework is done on a Python-based development environment, Jupyter Notebooks. Various APIs and functionalities from different libraries were used to develop the framework. The Yahoo Finance API, yfinance (), is used to get the historical and real-time data of cryptocurrencies. Two important functionalities in use to develop the framework are sklearn.preprocessing.RobustScaler () and tensorflow.keras.callbacks.EarlyStopping (), sklearn.preprocessing.RobustScaler () is used to scale features using statistics that are robust to outliers. This ensures precise standardization of the data tensorflow.keras.callbacks.EarlyStopping () is used to stop training when a monitored metric has stopped improving; this stops the wastage of computational resources. Some other libraries used were *numpy*, *pandas* and *seaborn*.

LSTM networks are employed in deep learning, a type of recurrent neural network (RNN) that can learn long-term dependencies, particularly in tasks involving sequence prediction. It has several hyperparameters that need to be set optimally for ideal results. LSTMs have a variety of applications, like price prediction, sentiment analysis, language modeling, speech recognition and video analysis. The application based on this paper is allied to price prediction for cryptocurrencies. The following sections highlight the use of the proposed *F-LSTM* model and its behavior using different performance parameters like loss, computation time, performance under different optimizers and memory utilization.

6.2. Performance analysis

6.2.1. Loss for *F-LSTM*

The loss measure refers to a statistic used to express the difference between the model's anticipated prices and the actual prices that were actually observed. The loss measure is used to gauge how well the LSTM model is doing in terms of its ability to predict outcomes. The LSTM model's performance on the training data—the dataset used to train the model—is measured by its training loss. A low training loss indicates the LSTM model is successfully picking up on and recognizing the patterns in the training set. On the other hand, An LSTM model's validation loss reflects how effectively it generalizes to data that it hasn't encountered during training. It is calculated using a distinct dataset from the training data called the validation dataset. The validation loss is a measure of the model's predicted performance on fresh or untested data. It helps in determining whether the model is capable of capturing fundamental data patterns without having to memorize the training samples. Figure 4 compares loss to validation Loss while training the model. In Figure 4, the x-axis indicates the measure of loss and the y-axis indicates the number of epochs during training. As depicted in Figure 4, loss and validation loss decrease with the increase in epochs. After robust training, the loss and validation loss converge well, which shows less over-fitting and a good model. The model, which is developed for the whole data set, is trained for a total of 50 epochs. The loss and validation loss start converging well after 10 epochs. By the end of 50 epochs, they have almost identical values, indicating minimal over-fitting in the trained model. The layers and the number of neurons have been aptly defined before training the model, due to which the model has been sufficiently trained, leading to minimal or no over-fitting. Another reason for such a minute level of over-fitting is that the model has been trained up to the right number of epochs.

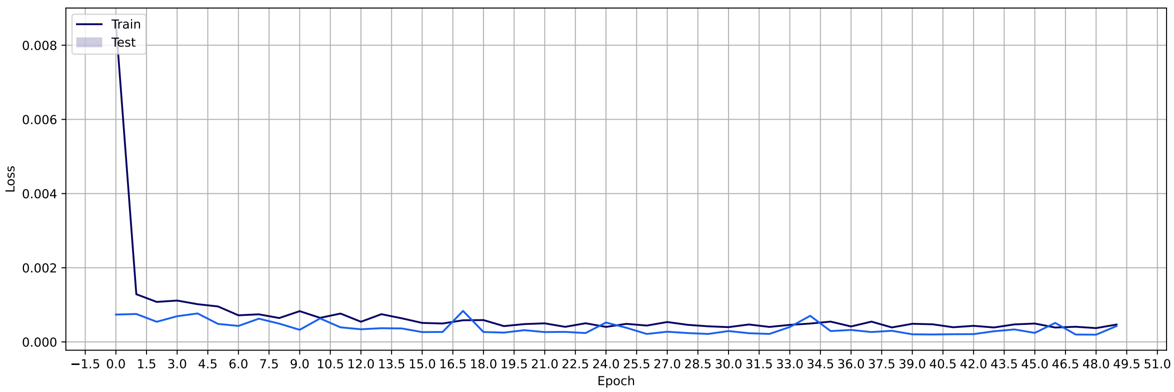


Figure 4. F-LSTM model loss.

6.2.2. Comparison of computation time between *F-LSTM* and LSTM

The amount of time needed to complete calculations and activities connected to developing, testing or generating forecasts using LSTM cryptocurrency price prediction models is referred to as computation time. It shows how long the underlying hardware and software took to do the necessary computations. Figure 5 shows the comparison of the computation time between the model developed for the whole data set and the client models used for federated learning, while, Figure 6 shows the prediction accuracy of the proposed framework. In Figure 5, the x-axis indicates the 2 different types of models and the y-axis indicates the computation time in seconds. In Figure 6, the x-axis indicates the timeline, and the y-axis indicates the actual price and prediction price for training and testing periods. Figure 5 clearly shows that the computation time utilized by the client models portrayed blue bar is significantly less than the computation time utilized by the model trained on the whole data set, represented by the green bar. It is also clear that the actual and predicted prices are almost similar, implying that the model has a high accuracy.

This is due to the distribution of data for the training of the local models. The time frame of the data used for the development of local models is 1 year for each client, whereas, the time frame of the data used to train the model trained on the whole data set is 5 years. More data would lead to a higher computation time, whereas fewer data would lead to a lower computation time. This makes FL a better and more efficient approach than the traditional one, as it saves computational time and resources. Hence, In federated learning, training is preferred as it is decentralized and carried out on client devices, allowing numerous devices to execute model updates in parallel. On the other hand, typical training involves training on the full dataset on a single machine, which can be slower due to the sequential processing of the data.

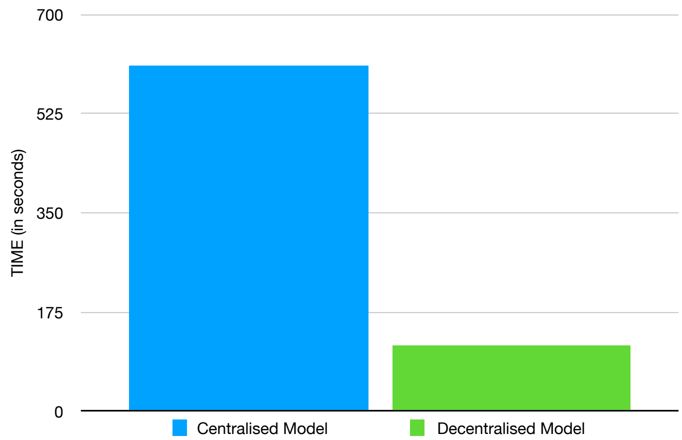


Figure 5. Comparison of computation time.

Figure 6. Prediction accuracy.

Another crucial element affecting the calculation time comparison between LSTM and F-LSTM, in addition to the data distribution and training durations, is the model update procedure. The communication overhead between the central server and clients is minimized with F-LSTM since model updates take place locally on client devices. This more efficient communication is particularly useful when working with clients with poor or limited connectivity. Traditional LSTM, on the other hand, uses centralized model updates and trains the entire model on a single machine. When working with huge datasets, this centralized processing can result in significant communication overhead. Additionally, the decentralized nature of F-LSTM enables asynchronous updates, allowing clients to update their models and speeding up training independently. These nuances in the update mechanism contribute to F-LSTM's superior computation time efficiency, making it a favorable choice for scenarios where efficient decentralized processing is imperative.

6.2.3. Performance under different optimizers

Optimizers are algorithms or methods used to modify the LSTM model's parameters (weights) while it is being trained. An optimizer's goal is to reduce the selected loss function by iteratively changing the model's parameters (weights) in accordance with the loss's gradients with respect to those weights. Figures 7 and 8 show the training and validation loss curve under different optimizers while training the proposed framework. In Figures 7 and 8, the x-axis represents the number of epochs and the y-axis denotes the measure of loss. The different colored curves are for the different optimizers. The different optimizers used are SGD, ADAGrad, RMSProp, Nadam and Adam. Adam gives the lowest loss and was used in the proposed framework.

On the basis of the gradients' average first and second moments, Adam changes the learning rate for each weight and bias parameter. Due to this, Adam is able to adjust the learning rate for each parameter, which results in faster convergence and better generalization. SGD is a basic optimizer that modifies the weights in accordance with the gradient of the loss function, but it has a slow convergence rate and is prone to local minima. Similar to Adam, Adagrad adjusts the learning rate for each parameter, but over time, it accumulates the square of the gradients, which may result in an excessively rapid decrease in the learning rate. The learning rate is also regulated by RMSProp, but it does so using a moving average of the squared gradients. Adam performs well for the proposed model for price prediction because it adapts the learning rate on a per-parameter basis, which leads to faster convergence and better generalization than other optimization algorithms.

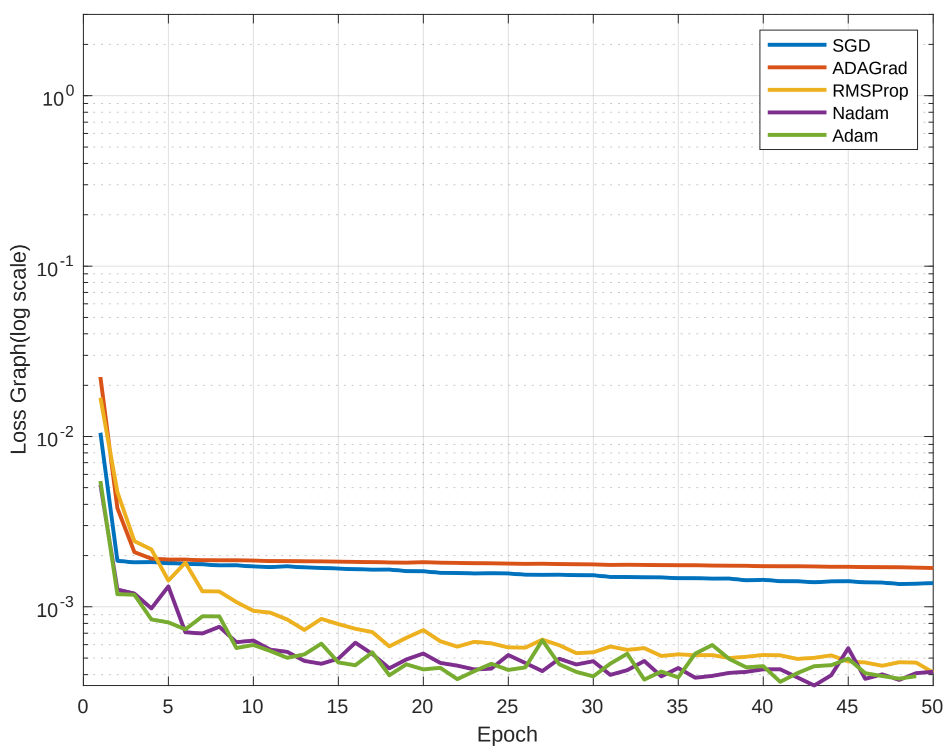


Figure 7. Loss for training under different optimizers.

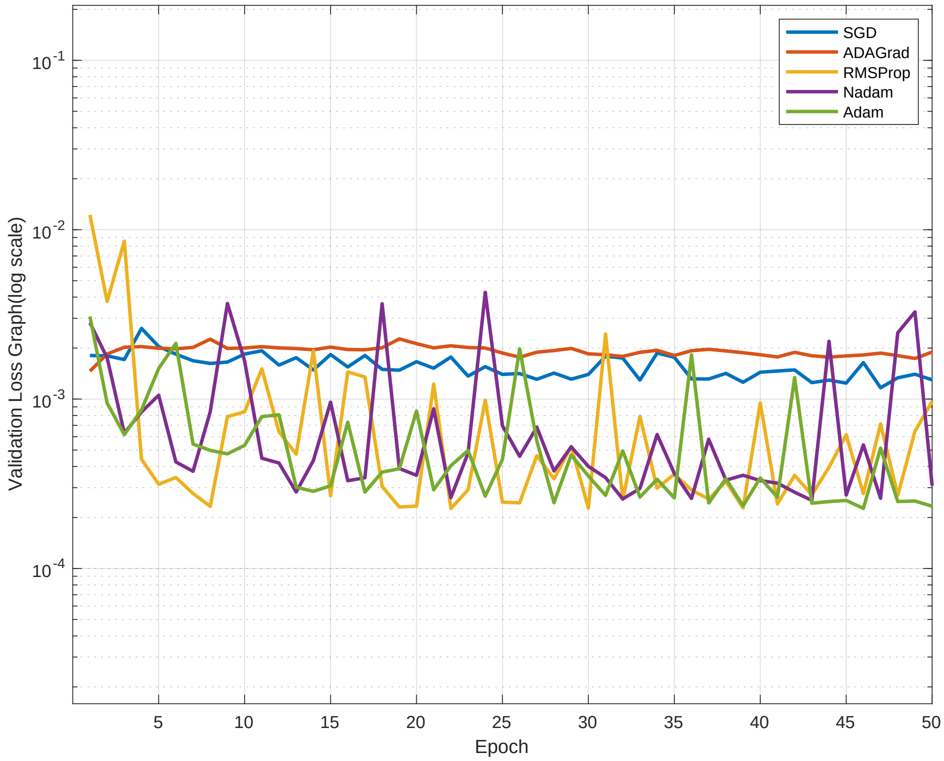
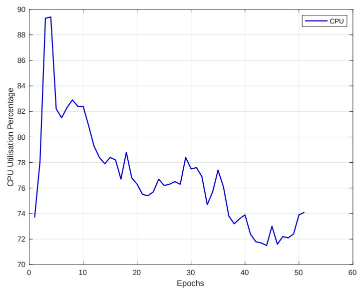


Figure 8. Validation loss for training under different optimizers.

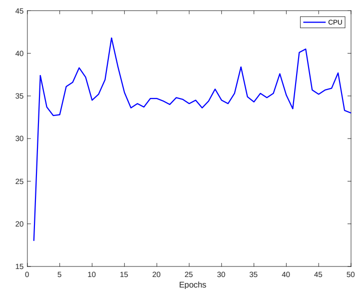
6.2.4. Comparison of CPU utilization between *F-LSTM* and LSTM

CPU utilization refers to the metric used to quantify how much the central processing unit (CPU) is used when the model-related computations are carried out. It calculates the proportion of time the CPU is used to do LSTM model-related operations, such as training, evaluating, or making predictions. Figure 9(a)–(f) show the comparison of the CPU utilization between the model developed for the whole data set and the local models used for federated learning. In the figures, the x-axis indicates the time intervals and the y-axis indicates the CPU utilization. It is evident that the local models trained for FL utilize significantly less computation power than the model trained on the whole data. The CPU utilization for training the client models is almost half of the CPU utilization during normal training.

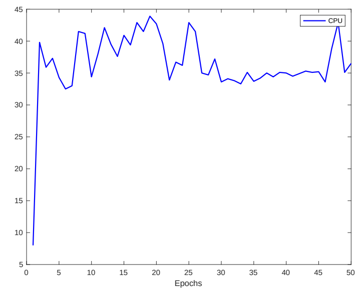
In contrast to a normal centralized training situation, the client models in FL often execute a small amount of computation. This is a way that each client can undergo training using a smaller subset of the data rather than the complete dataset when employing federated learning. The quantity of data transport and processing required is lowered since the client models submit only their updated model parameters (weights) to the central server as opposed to providing the whole dataset. Additionally, before sending the model weights to the central server, FL involves compressing them. As a result, the amount of data provided is smaller, which also lowers the computational demands on the client models. Hence, FL training uses only a fraction of the computational resources used during normal training.



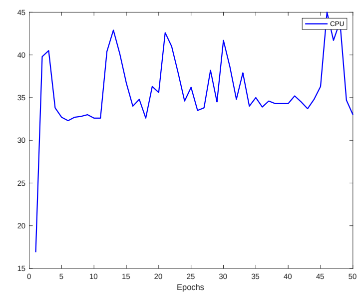
(a) Resource utilization for dataset.



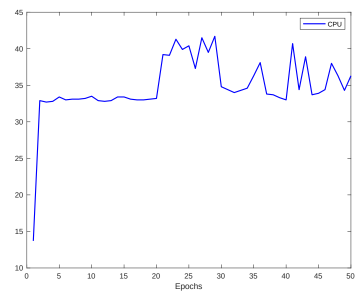
(b) Resource utilization for client 1.



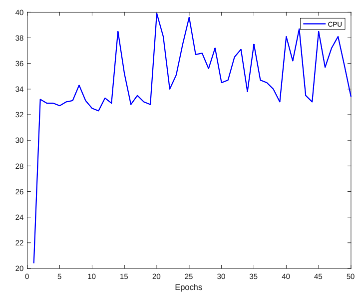
(c) Resource utilization for client 2.



(d) Resource utilization for client 3.



(e) Resource utilization for client 4.



(f) Resource utilization for client 5.

Figure 9. Performance of resource utilization for clients and normally trained model.

The resource utilization in traditional centralized training is significantly high, at about 74%. This is expected given that all computations, model updates and data processing are done on a single system, which takes a lot of resources. On the other hand, the FL method shows much greater resource efficiency. For the training of the 5 client models, roughly about 34% of the CPU resources were utilized. This significant decrease in resource use is a direct result of FL's decentralized structure. Through localized model updates on each client's own data, FL enables parallel processing and decreased resource requirements for each client. This fits with the fundamental ideas of distributed computing when analyzed theoretically. FL makes use of the parallelism that comes with training many models over distributed nodes, which leads to greater efficiency in resource management. This finding strongly suggests that the FL method is more resource-efficient than conventional centralized training. It not only lessens the pressure on individual devices but also highlights the possibility for large computational cost reductions, which makes FL an appealing option, particularly in situations where resource limitations are an issue. Thus, the results from Figure 9 offer strong support in proving that the FL scheme outperforms conventional training in terms of resource utilization.

6.2.5. Comparison of memory utilization between *F-LSTM* and LSTM

In the context of LSTM cryptocurrency price prediction models, the term memory utilization refers to the metric used to evaluate how much memory or memory resources were used during model training, evaluation or prediction. The memory needs of the LSTM model and related calculations are quantified. Figure 10 shows the comparison of the memory utilization between the model developed for the whole data set and the local models used for federated learning. In the figures, the x-axis indicates the different models and the y-axis represents the memory utilization. It is evident that the local models trained for FL utilize significantly less memory than the model trained on the whole data, as their file sizes are significantly smaller.

As FL uses a distributed training approach that involves training multiple models on different subsets of the data rather than one model on the entire dataset, client models trained for FL significantly use less memory and have smaller file sizes than models trained on the entire dataset. A small portion of what would be needed to train a centralized model is used by each client device to train its model. In comparison to the centralized model that would be trained on the entire dataset, this leads to smaller models that utilize less memory and have smaller file sizes. Furthermore, FL models are often created to be compact and optimized for client devices with low resource requirements.

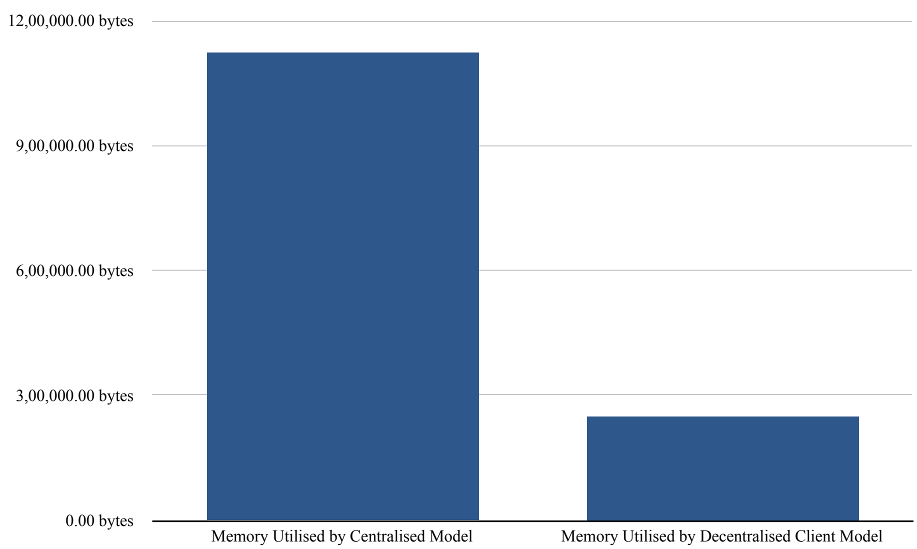


Figure 10. Memory utilization comparison.

6.2.6. Comparison with other FL schemes

Federated learning has emerged as a pivotal paradigm in the field of distributed learning for training models across decentralized clusters of nodes and updating model parameters in an optimized way. Within this realm of distributed learning, the three prominent averaging algorithms for updating global model weights are FedAvg, FedSGD and FedDyn, These schemes propose unique alignment for updating and averaging the client weights for global model learning. The respected schemes can be understood as follows.

1) *FedAvg*: The central server calculates the weighted average of the received updates from all the selected devices. Each update is weighted by the number of data samples that the device used for training. Devices with larger datasets contribute more significantly to the global model. The mean average percentage error while training the global model using FedAvg is 1.34% (as shown in Figure 11).

2) *FedSGD*: The averaging is done exactly the same as that of FedAvg but while updating the global model, that is done using the aggregated gradients. This update is performed using the stochastic gradient descent (SGD) algorithm or its variants, where a learning rate controls the step size of the update. The mean average percentage error while training the global model using FedSGD is 12.55%.

3) *FedDyn*: Instead of sending gradients or model updates directly, devices in FedDyn share information about the dynamics or changes in their local models. This information might include parameters like momentum, velocity or other relevant statistics. These Dynamics are used instead of the weights of the models for global model updation. The mean average percentage error while training the global model using FedDyn is 12.04%.

The wide difference in losses that occurred is particularly because of the notion in which the algorithm is applied. As for sequential learning parameters, the FedAvg performs better than others because of the weighted aggregation of client servers paired up with *Adam* optimizer, which catalyzes the process of finding the minima for the cost function while training the model.

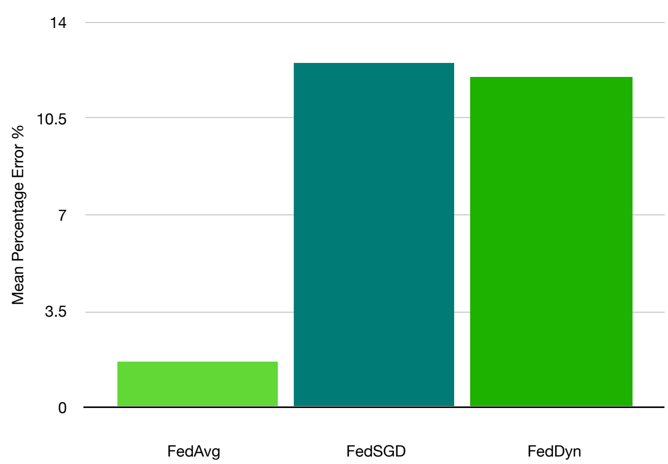


Figure 11. Comparison between different FL schemes.

6.2.7. Error measures

Assessing the effectiveness and reliability of any machine learning or statistical model requires measuring its prediction accuracy with high precision. Hence, researchers rely on error measures such as loss measures or performance metrics in their analysis. By quantifying the variance between actual values and predicted ones these metrics enable us to assess how accurate and reliable a given model's performance is getting over time. After training the global model for 10 epochs, the *F-LSTM* model was evaluated using three error measures which are, Median Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Median Absolute Percentage Error (MDAPE). The model's Median Absolute Error (MAE) score is 91.98 percent, which means that on average, the predictions differ marginally from the measured data. This shows that the model performs fairly well in terms of absolute error.

The model's ability for precise prediction improves with decreasing MAE. The Mean Absolute Percentage Error (MAPE) of 6.23 percent shows that the model's predictions often deviate from the actual values by about that percent. This portrays that, given the size of the target variable, the model's performance is fairly accurate. A lower MAPE indicates that the model is more capable of making accurate predictions. The Median Absolute Percentage Error (MDAPE) of the model is 5.1 percent. This demonstrates the model's accuracy since a lower MDAPE implies greater prediction precision. The model's consistency in producing predictions that are close to the actual values illustrates both its dependability and its effectiveness. The model's effectiveness is demonstrated by the excellent results it produces after training on only 10 epochs. The model exhibits a streamlined and resource-efficient learning procedure by successfully resolving dependencies through small-batch training on the complete dataset for a limited number of epochs.

7. Conclusions and future works

In conclusion, this study marks a substantial advancement in the field of predicting cryptocurrency prices. Our innovative method completely transforms the predictive analytics environment in this dynamic and privacy-sensitive field by integrating LSTM with FL. Our approach takes advantage of the distributed data-gathering capabilities of FL to improve the pattern recognition performance of LSTM by collecting data from decentralized nodes while adhering to tight privacy measures. Without the requirement for centralization, this combination produces a richer dataset, which leads to remarkable efficiency throughout the training stage. Our methodology proves its ability to deliver extremely accurate cryptocurrency price projections, with training loss converging to an amazing minimum of 2×10^{-4} and validation loss resting at an amazing 2.3×10^{-4}.

Our federated integrated LSTM model also complies with current edge computing trends, making it more than just an advance in cryptocurrency price prediction. It improves operational efficiency and, more importantly, satisfies the fundamental principles of data privacy and security by executing computations closer to the sources of the data. As we shift our attention to a comparison with traditional approaches, like LSTM, ARIMA and GARCH models (all evaluated on the same dataset), the findings highlight the significant advantages of our strategy. Our approach not only performs admirably in terms of loss reduction, but it also demonstrates fantastic computing efficiency. It is crucial to understand the broader implications of our findings by looking beyond the metrics. Our approach gives traders, investors and financial analysts a strong tool to help them make judgments at a time when cryptocurrencies are having an increasing impact on financial markets. Furthermore, our focus on preserving data security and privacy in the age of data-driven finance is further demonstrated by our commitment to the federated method. Our study paves the way for more accurate, effective and privacy-respecting cryptocurrency price projections as we look into the future. It claims to revolutionize financial decision-making by providing a way to more trustworthy insights and well-informed actions in the intricate and constantly changing world of the cryptocurrency markets.

We are resolutely devoted to improving our *F-LSTM* framework on numerous fronts in future works, hoping to deliver solid answers and insights in the field of cryptocurrency price prediction in order to address the research deficiencies found in our current study. First, in order to give the model the dynamic versatility needed to thrive in the constantly shifting real-time cryptocurrency environment, we intend to optimize its integration with reinforcement learning. The accuracy and responsiveness of cryptocurrency price projections will be improved by this improvement, which will enable our framework to take proactive actions in reaction to market swings. Second, we want to extend the F-LSTM schema's range of applications by using it with different cryptocurrencies, offering a sectorial and application-centric viewpoint. We seek to increase our understanding of how various cryptocurrencies behave and react to comparable prediction approaches by analyzing a variety of digital assets, each with its own distinct market dynamics. This will eventually lead to more specialized predictive models. Finally, we are looking into how split learning and lightweight encryption techniques can be applied to the analysis of cryptocurrency price data. Split learning has the potential to improve data security and privacy, particularly in a field where data protection is crucial. Also, applying lightweight encryption to the trained weight can enhance the security and privacy measures of the proposed work. This study demonstrates our dedication to increasing cryptocurrency markets' accuracy and data security by taking a diverse approach to comprehend better and forecast the prices of digital assets.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflict of interest.

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RESEARCH ARTICLE

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Convolutional neural network and unmanned aerial vehicle-based public safety framework for human life protection

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Summary

In this paper, we developed an object detection and identification framework to bolster public safety. Before developing the proposed framework, several existing frameworks were analyzed to bolster public safety. The other models were carefully observed for their strengths and weaknesses based on the machine learning and deep learning algorithms they operate on. All these were kept in mind during the development of the proposed model. The proposed framework consists of an unmanned aerial vehicle (UAV) utilized for data collection that constantly monitors and captures the images of the designated areas. A convolutional neural network (CNN) model is developed to recognize a threat and identifies various handheld objects, such as guns and knives, which facilitate criminals to commit crimes. The proposed CNN model comprises 16 layers with input, convolutional, dense, max-pool, and flattened layers of different dimensions. For that, a benchmarked dataset, that is, small objects handled similarly to a weapon (SOHAs), a weapon detection dataset is used. It comprises six classes of 8945 images, with 5947 used for training, 1699 used for testing, and 849 used for validation. Once the CNN model accomplishes the object identification and classification, that is, the person is criminal or non-criminal, the criminal is forwarded to various law enforcement agencies and non-criminal data are again forwarded to the CNN model for improvising its accuracy rate. As a result, the proposed CNN model outperforms several pre-trained models with an accuracy of 0.8352 and a validation accuracy of 0.7758. In addition, the proposed model gives a minimal loss of 0.83 with a validation loss of 0.97. The proposed framework decreases the burden on crime-fighting agencies and increases the accuracy of crime detection. Additionally, it ensures fairness and operates at a meager computational cost compared to similar pre-trained models.

KEYWORDS
convolutional neural network, deep neural network, human life protection, public safety, unmanned aerial vehicle

1 | INTRODUCTION

Public safety is a pivotal part of society, ensuring citizens' safety, and is the top priority of every government or regime. Each government has established various means and measures to safeguard its citizens, that is, article amendments in the law. Public safety contributes to a large part of the life index of any nation and is essential for its citizens' holistic and economic development. Various systems like deploying unmanned aerial vehicles (UAVs), surveillance cameras, and police patrolling are arranged by the governments to protect citizens from crimes. Nations also established various public safety organizations/agencies to protect citizens from crimes. But, for many nations (having large populations), ensuring public safety is quite challenging for many reasons. The major reason for this is the overburdened public safety-enhancing organizations. There isn't enough manpower per unit population for these organizations to work efficiently. So, for overly populated countries, fighting crime is considered too tedious for crime-fighting agencies. Sometimes, these agencies can also need more required infrastructure and funds. To add to these issues, the relationship between the common public and the officers of the aforementioned agencies could be more optimal too.

In the aforementioned view, several researchers presented various solutions that ensure public safety.[1–4] These solutions include using existing technologies like artificial intelligence (AI), deep learning (DL), blockchain technology, and cloud computing for crime identification and public safety. Among the aforementioned technologies, AI and DL are prominent in providing safety solutions by predicting or analyzing crime scenes.[5] Cloud computing makes it relatively simpler for crime-fighting agencies to work in synchronization with federal policies and helps avert security breaches and leakage of sensitive information. At the same time, there are many unsolved problems that cloud computing faces while dealing with public safety, like, compromised privacy and security, compliance with all rules and regulations, recovery of lost data in contingency, and high establishment costs. Neto et al[6] and Sultana and Wahid[7] proposed a fog-based video surveillance for security management and an Internet of Things (IoT)-based smart transportation system. The fog-based framework has been used to interact with IoT devices and the edge network with the remote cloud. It provides agile and accurate weapon detection, but the systems suffer from issues that would make them unwise to use practically. The drawbacks are high networking traffic, massive storage, and the required network resources. The systems are also solely dependent on the ability to stay connected to the cloud, which, if compromised, would make the whole system redundant. On the other hand, blockchain technology has a fair share of advantages and disadvantages when trying to improve public safety. Li et al[8] proposed a blockchain-based lawful evidence management scheme for digital forensics that support transparency, immutability, and auditability when managing such lawful evidence. Tsai[9] highlighted the application of blockchain technology for the criminal investigation process. Researchers utilize blockchain technology to aid digital forensic tasks concerning preliminary investigation, case management, and court phases. Blockchain provides improved safety, secure storage of data, and integrity while investigating, leading to enhanced public trust. But, simultaneously, it has problems like huge energy and cost requirements. Moreover, the blockchain has the benefit of immutability, which ensures the data, once recorded, cannot be deleted by anyone. UAVs can be pivotal to public safety, continuously sending live images of crime scenes or incident locations.[10] UAVs reduce human intervention and make the investigation process seamless and reliable. It can monitor streets from the air, making patrolling more efficient than humans.[11] Gur et al[12] and Karim et al[13] presented image processing-based approaches using UAVs to detect crimes on streets. Several things the authors have suggested, like using the latest graphic cards, using smaller drones for compact and congested streets, and integrating GPS systems to boost performance. They ensure the practicality of UAVs in detecting and preventing prevalent street crimes.[14]

Various aforementioned solutions related to public safety can be enhanced by integrating AI algorithms. It helps ease the citizens' safety and makes communities safe. It can support criminal investigations, predict organized crime by analyzing patterns, and help combat severe threats. He and Zheng[15] presented research that predicts crime rates in urban neighborhoods using the DL-based generative adversarial network (GAN) algorithm. The authors generate crime heat maps for a city and quickly examine the areas where the crime rate is too high. This helps law enforcement agencies to act. Their proposed model needs to pinpoint the location of a crime, which would leave officers short-handed. Further, the focus is on crime rate prediction, not protecting against crimes. So there is still scope for AI to analyze enormous amounts of data and reliably recognize patterns and connections between recorded crimes. Further, as per the literature, no existing approaches identify crimes based on the images captured from different sources and their locations. With these understandings, a gap between crimes and convictions can improve understanding of behavior patterns and sequences of events that contribute to crime.[16] This gives law enforcement agencies a head start in developing strategies to obstruct certain pathways related to public safety.

Motivated by the aforementioned gaps, this paper proposes a customized convolutional neural network (CNN)-based framework to assist law enforcement agencies in protecting crimes and ensuring public safety. The proposed framework detect street crimes by analyzing the captured images from the deployed UAVs and identifying patterns and sequence of crime events. UAVs constantly monitor citizens and the objects they carry. The captured images are fed as input to the proposed model to classify them into criminal or non-criminal categories by identifying the objects involved in the image. If the framework finds any weapons in the picture, the crime-fighting agencies are imminently informed to act and defend the public. The proposed model substantially decreases the burden on crime-fighting agencies while increasing the accuracy of crime detection and ensuring fairness as the process becomes automated. Additionally, it operates at a significantly lower computational cost than other pre-trained models performing a similar function, which makes it extremely cost-efficient.

1.1 | Research contributions

The following are the contributions of this paper.

- We proposed a CNN-based learning framework that assists law enforcement agencies in detecting crime. It decreases the burden such organizations face by reducing human intervention and potentially improves the accuracy of crime detection.
- To increase the efficiency and accuracy of the proposed framework, an optimized CNN is developed to avoid bias and ensure fairness in detecting crime patterns from the dataset. It updates the image database with every prediction by adding new instances to the dataset; this improves the overall detection rate of the CNN model.
- The computation cost and memory utilized by the proposed framework are significantly less than other pre-trained models like VGG19, Inception V3, and ResNet101, which makes it highly efficient and cost-effective to use. The proposed model's file size is also minuscule compared to other pre-trained models.
- Further, several evaluation metrics, such as accuracy, loss, and optimizer's performance, are used to evaluate and test the CNN model. The model is developed by running many image combinations, outperforming other trained models, such as VGG19, Inception V3, and ResNet101.

1.2 | Organization

The organization of this paper is as follows. Section 2 describes the related works in the field of public safety. Section 3 presents the system model problem formulation. Section 4 presents the proposed CNN-based framework for crime identification and detection. Section 5 emphasizes the result and discussion of the proposed framework. Finally, Section 6 concludes the paper.

2 | STATE OF THE ART

This section discusses the related work carried out by researchers in public safety and crime identification. The crime rate and detection have increased significantly with ever-changing societies and technologies. Traditional approaches for public safety record crime and classify the rate, which is duly based and dependent on the text and record-based systems. With technological advancements, crime detection and classification can also be performed on photos, proof of physically performed, and recorded crimes. Researchers have proposed many ML- and DL-based techniques to classify and predict crimes. For example, Tasnim et al[17] show the implementation of time-series analysis of the data using the long short-term memory (LSTM) model to explore and predict the data outcome. They have used natural-level processing to combine the output of different models into one for the prediction of the classes. However, the model has limited classes and cannot extend its capabilities if another class is added.

Then, Baek et al[18] proposed a novel approach for classification using support vector machine (SVM) and deep neural network (DNN) algorithms. Among these models, DNN gave a better error rate than SVM with better training accuracy. However, the model could not perform well in validating the trained model, thus overfitting to an extent. Safat et al[4] proposed a nascent approach that combined the features and capabilities of different models to predict the output considering many features of the dataset used with a good diagrammatic representation of insights. However, their approach is an exploratory dataset analysis without making a classification prediction of the required data. Kshatri et al[19] proposed an empirical analysis of the dataset using ML techniques, such as stacking, boosting, and ensemble classifiers for predicting and classifying the target attribute with the consideration of numerous predefined attributes. Their model reflected a better overall accuracy for the classification problem.

Han et al[20] presented an approach to forecasting cities with greater crime rates and predicting the outcome concerning the record of the past times. They have classified cities in the United States with selected attributes accurately. However, the training of the model is limited to certain variables only. Wang et al[21] proposed a model for the ACP approach with a considered construction of an artificial crime scene and gave an empirical analysis for the parallel crime scene. However, the model is too ideal and doesn't implicate the practical implementation. Zhang et al[22] presented an LSTM-based model that uses geospatial data for identifying adaptive attributes, which are further used for multi-class classification of cities with the greater crime rate and further prediction using several AI algorithms. However, appropriate accuracy is not achieved with their proposed model.

Mohammadpour et al[23] stress the significance of utilizing DL techniques in network intrusion detection systems because of the sophistication and increased complexity of contemporary cyberattacks. They examine a number of studies that used CNNs for NIDS, including those that used more modern architectures like residual networks and attention-based models, as well as models built using conventional convolutional layers. The authors also review many datasets utilized in CNN-based NIDS research, including the NSL-KDD and KDD Cup 1999 datasets. They discuss the problem of unbalanced datasets in NIDS and how some research has dealt with it using methods like data augmentation and oversampling.

Anand et al[24] examine several research that have applied CNNs and other DL techniques to network traffic and Android applications, among other contexts, to detect malware. They also talk about the drawbacks of these methods, such as the necessity for a lot of labeled data, the possibility of adversarial assaults, and the difficulty of understanding the judgments made by DL models. The authors also discuss recent advancements in DL-based malware detection, including ensemble approaches and transfer learning. They also emphasize how crucial it is to consider the resource limitations of healthcare apps, such as their constrained memory and processing capabilities, when constructing DL models for malware detection. Table 1 describes the relative comparison of state of the art approaches with the proposed one.

Through the comprehensive understanding and realization of all the recent approaches, the appropriate and optimized use of CNN was not implemented in a dynamic and real-time environment. The approaches were static to the available data without continuous updates for data generated over time. Thus, the proposed framework is a customized CNN classification and prediction model, which combines the working of DNN and CNN models in making appropriate predictions on the image datasets with multiple classes. The proposed framework identifies features of different images from the respective classes and extracts unique attributes related to the particular image. The parameters are updated and controlled with appropriate values to achieve the best result, such that possibilities of vanquishing and exploding gradients are reduced to a minimum. The framework is also open for fine-tuning over the layers for further adaptability with the dynamics of the evolving environment. Thus, combining CNN and DNN with tuned hyperparameters improves the training and validation accuracies with a justified loss convergence. The model is adaptive overall if additional classes are to be added later for training and classification purposes.

3 | SYSTEM MODEL AND PROBLEM FORMULATION

This section presents the system model and problem formulation of the proposed DNN- and CNN-based framework. Despite recent improvements in the public safety domain, several crimes are still committed and unable to predict and classified priorly. Although the crime rates are decreasing, the grassroots reality is gloomy. The most common crimes that happen every day include larceny or theft, burglary, aggravated assault, and robbery. The proposed system model deals with this problem and aims to reduce crime rates and increase public safety. In the proposed system, the civilians set is represented as $\{U_1, ..., U_i, ..., U_j, ..., U_m\} \in U$, where a civilian can be a criminal or a non-criminal based on whether they are carrying weapons (probable criminal) or not, whereas the set $\{K_1, ..., K_i, ..., K_j, ..., K_m\} \in K$ represents the weapons set. This criminal activity is captured by UAVs, $\{D_1, ..., D_i, ..., D_j, ..., D_m\} \in D$, which are deployed by agencies responsible for ensuring public safety.

TABLE 1 Comparative analysis of the proposed framework with the existing state-of-the-art schemes for public safety.

Authors	Year	Objective	Algorithms used	Pros	Cons
Tasnim et al.[17]	2022	Presented a transfer learning for predicting crime rates of two different cities in the United States (US) by performing exploratory data analysis on the data, returning better results than the current state of the arts	LSTM and NLP	Good precision and recall values	Limited to a small number of predefined classes
Baek et al.[18]	2021	Presented a combinational technique for making real-time predictions by employing CNN and DNN in the model architecture, overtaking the conventional approach of using SVM and Naive Bayes for ML predictions	CNN and SVM	Good training accuracy	Overfitting for large datasets
Safat et al.[4]	2021	A comparative method for forecasting the crime rates of two major cities of the US by performing time-series analysis on the dense data to show the versatility of DL and ML algorithms to predict promising results	LSTM and ARIMA	Fusion model for classification and time-series analysis	Performance limited to EDA with limited scope
Kshatri et al.[19]	2021	Among many established ML algorithms available in the domain, an efficient architecture performing well in both metrics of measure for time complexity and better accuracy than others	Ensemble and boost classifiers	Good overall accuracy	Limited to a small number of predefined classes
Han et al.[20]	2020	Identify the recurrent patterns of crimes occurring in geospatial regions using LSTM network and classify different regions with their respective crime rates over time	LSTM and STGCN	Optimized classification using spatiotemporal data	No accuracy measure and limited to a small number of predefined classes
Wang et al.[21]	2018	Incorporating human behavior characteristics and another stochastic factor for comparative predictions of the crime scene using artificial societies, computational experiments, and parallel execution (ACP) approach	ACP approach	Good software-defined analysis	Excessively theoretical for practical usage
Zhang et al.[22]	2020	Incorporate various ML algorithms for predicting the major crime hot spots and depicting the visual analysis of the predicted results	LSTM, KNN, random forest, naive Bayes, and CNN	Geospatial data used for classification; comparing models	High computational resources used and low accuracy
The proposed work	2023	Optimized CNN-based approach to enhance public safety	CNN and DNN model	Fusion of CNN and DNN; good training and validation accuracies	-

Equations (1) and (2) represent that a civilian can possess one or more weapons.

$$\exists U_i \in U \xrightarrow{has} K_i \in K \Leftrightarrow \{U_i, K_i\}, \tag{1}$$

$$\exists U_i \xrightarrow{has} \{K_2, K_3, ..., K_j\} \in K. \tag{2}$$

In Equations (3) and (4), if a civilian possesses a weapon, he is categorized as a criminal; otherwise, non-criminal.

$$U_i \cap K_i \neq \emptyset \rightarrow Criminal, \tag{3}$$

$$U_i \cap K_i = \emptyset \rightarrow Non\text{-}Criminal. \tag{4}$$

UAVs capture criminal acts and send these images to public safety agencies for further action, represented using Equation (5).

$$\{U_i, K_i\} \neq \emptyset \rightarrow D_i. \tag{5}$$

As mentioned in Section 2, many machine learning algorithms are already applied to ensure public safety and predict the actions required to reduce crime rates, although many of the prescribed algorithms are inefficient to work in a real-time environment. The need for a CNN algorithm is highlighted to be integrated into the UAVs to identify and detect real-time on-sight criminal activities. As its dynamics of detecting and classifying multiple frames of images give greater efficiency and flexibility for predictions in the real-time environment.

The CNN architecture variably changes its computation weights to ensure optimum accuracy. The CNN dynamics are based on the concept of back-propagation through the layered computation and reconfiguring the weights of the kernels, which are applied to input images decreasing the error over the span of time. Thus, in real time, the approach of using CNN does not take a long time to predict and classify the activities captured by the UAV.

The objective of the proposed system model is to identify civilians U_i who possess weapons K_i and report them to law enforcement agencies. Existing crime detection schemes work and catch criminals, but not at an efficient rate, as it involves human discretion instead of technology. There are latency issues in the current systems and no proper weapons detection. The proposed framework offers accurate weapon detection and crime prediction. Another advantage this provides is that it can also define the intensity of the crime, which would make it easy for law enforcement authorities to prioritize in case of multiple crimes being committed.

In this viewpoint, the proposed framework aims to maximize the weapon detection rate from the captured images at the crime scene. Equation (8) shows the objective function of the proposed framework, where $\mathcal{F}$ is the objective function, whereas Y_{Z_i} portrays different instances of data requests and Ψ represents the CNN model.

$$X_1 = \max \sum_{i=1}^{m} \text{Detection}_\text{R}\text{ate}(\Psi), \tag{6}$$

$$X_2 = \max \text{Secure}(Y_{Z_i}), \tag{7}$$

$$\mathcal{F} = X_1 + X_2. \tag{8}$$

$$\begin{aligned}
&s.t.\\
&C1 \quad : Y_{Z_i} \geq 0, \forall i \in \{1, 2, ..., m\},\\
&C2 \quad : X_1 \geq 0,\\
&C2 \quad : Y_{Z_i} \in D_i.
\end{aligned}$$

4 | THE PROPOSED FRAMEWORK

This section describes the working of the proposed CNN model Ψ for public safety and crime identification (shown in Figure 1). The framework is divided into three distinct layers: the data, AI, and application. The functionality of each layer is described as follows.

4.1 | Data layer

Numerous UAVs $\{D_1,...,D_i,...,D_j,...,D_m\} \in D$ are involved in the data layer, which can be used for patrolling over the city and capturing suspicious scenes. UAVs transmit real-time images and forward them to the proposed classification framework (CNN model). From the images, it is to determine whether any criminal act performed by the users $\{U_1,...,U_i,...,U_j,...,U_m\} \in U$ and classify them as criminal or non-criminal. This is determined by whether or not the user possesses any weapon $\{K_1,...,K_i,...,K_j...,K_m\} \in K$ in the image. The data are captured in images and is further forwarded to the AI layer, which makes predictions.

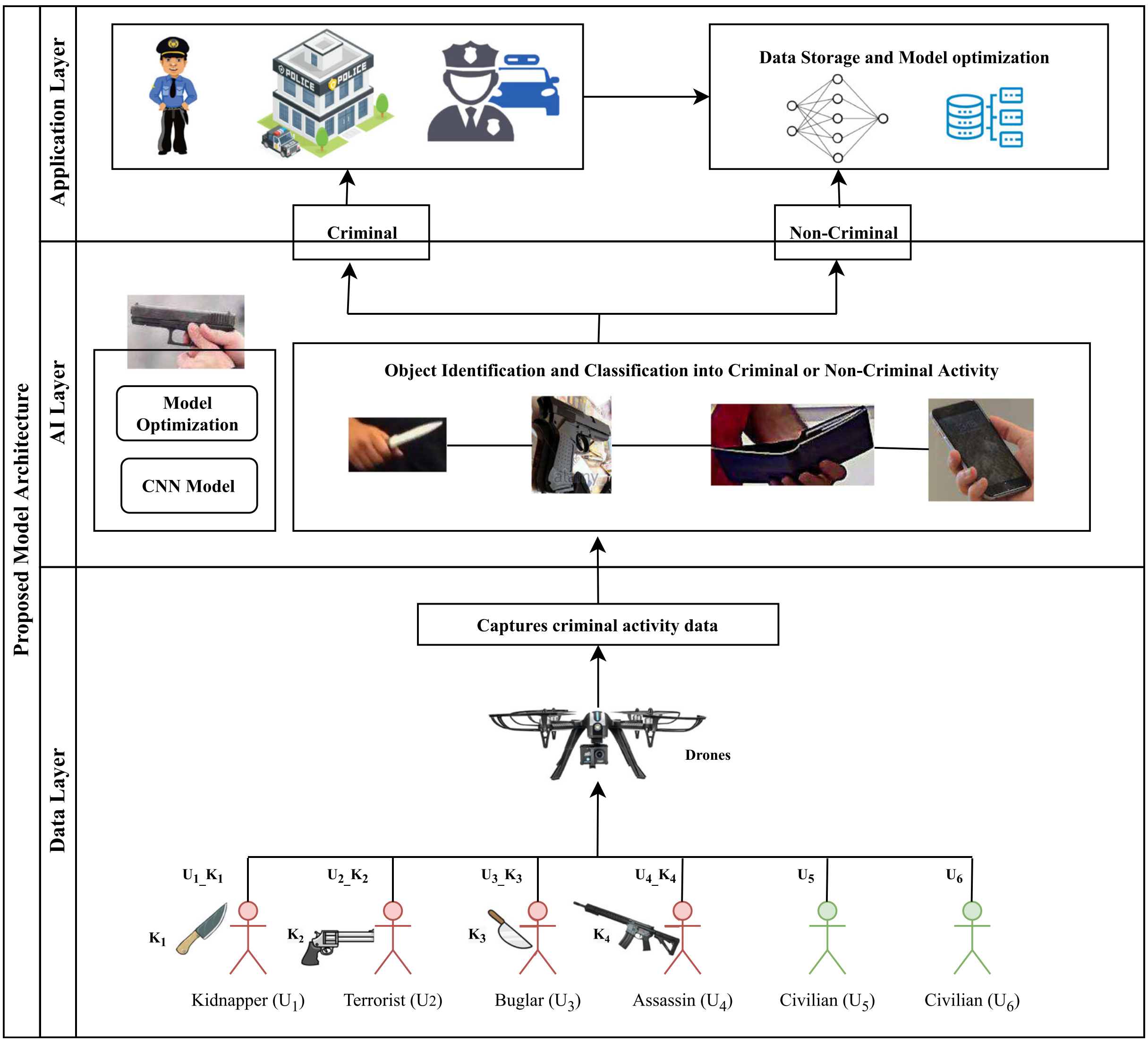

FIGURE 1 Proposed system model.

4.2 | AI layer

This layer's task is to make predictions and classify images based on the data received from the data layer. The AI layer comprises an object detection CNN model, prepared after data preparation and prepossessing, and can make predictions.[25] Figure 2 shows the sequential flow of the proposed framework for UAV-based public safety for human life protection.

4.2.1 | Dataset description

The dataset used to train the proposed weapon identification and classification framework is the small objects handled similarly (SOHAs) weapon detection dataset. It comprises images of weapons and other small objects handled in the same way as weapons. This dataset consists of six object classes: pistol, knife, bill, purse, smartphone, and card. The dataset consists of 8945 images, and the number of images in each class is mentioned in Table 2. In the proposed system, there are numerous sets of images, $\{I_1, ..., I_i, ..., I_j, ..., I_m\} \in I$, which are present in different directories; correspondingly, they are assigned their respective labels according to the directory they are present in such as $\{L_1, ..., L_i, ..., L_j, ..., L_m\} \in L$. The dataset δ with the use of scaled iterator is divided into batches of size 32 such that the respective images and corresponding labels are allotted within a particular batch which can be further used for training the neural network represented as follows.

$$\{I_1 L_1\} \to B_1, \tag{9}$$

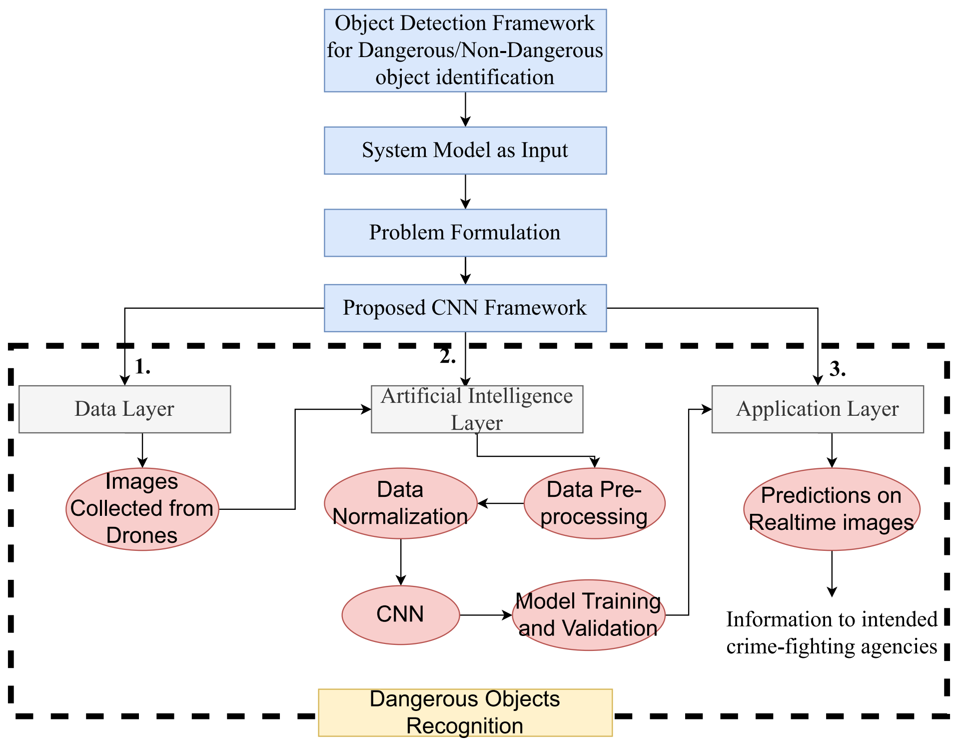

FIGURE 2 Sequential flow of the proposed framework.

TABLE 2 Number of images in each class.

Class Name	Pistol	Knife	Bill	Purse	Phone	Card
Number of images	3710	2170	688	784	1184	409

$$\{I_2 L_2\} \rightarrow B_2, \tag{10}$$

$$\{I_m L_m\} \rightarrow B_m. \tag{11}$$

4.2.2 | Data preprocessing

Firstly, we keep the data δ on the cloud storage and load it further for preprocessing for improved training and prediction values. Initially, the data were scaled to a standard value with all the pixels of an image between 0 and 1 for handling outliers of certain exceptions. The mathematical representation of scaling is described as follows.

$$\delta \rightarrow (x,y) \rightarrow \left(\frac{x}{255},y\right). \tag{12}$$

Equation (12) represents the mapping and scaling of data, where x is the variable used to denote the tensors comprising values of pixels of images and y is the variable used to denote the label of class an image.

Following tensors, we performed data augmentation using various configurations of image properties like saturation, alignment, brightness, and adjusting contrast. We also elaborated on a particular section of the image that should be focused on for detection. After data augmentation, the images are divided into batches. Each batch comprises 32 images. The *scaled_iterator* is used over the randomized set of images while dividing images into batches to ensure that no image is repeated in consequent batches. A total of 280 batches are formed. These batches are divided into three categories: training, testing, and validation.

$$T_t = \delta \times 0.6, \tag{13}$$

$$T_s = \delta \times 0.1, \tag{14}$$

$$T_v = \delta \times 0.3 + 2. \tag{15}$$

Equations (13)–(15) represent the division of batches, where T_t represents the number of batches for training, T_s represents the number of batches for testing, and T_v represents the number of batches for validation.

4.2.3 | Model motivation

Based on our analysis in Section 2, most pre-trained CNN-based architectures like VGGNet19, ResNet101, and InceptionV3 are used for the proposed model's application. These pre-trained models are trained on the *ImageNet* dataset. We found several drawbacks during the analysis of these models. Figures 3 and 4 show the relative comparison of the proposed framework with the other pre-trained models which are discussed. These models have many layers, as shown in Figure 3, which increases the number of neurons involved in the network. Hence, increasing the trainable parameters, as cited in Figure 4. Due to this, the time and cost of training the model are exponentially higher than that of the proposed model. Considering the financial constraints law enforcement organizations face in developing nations using these pre-trained models is practically unfeasible in the real-world scenario. The pre-trained models also tend to overfit while training. This inspired us to develop the proposed framework, which outperforms the aforementioned models considerably while having only 14 layers and a considerably less number of trainable parameters, hence using way fewer computational resources.

The proposed CNN model is developed after multiple implementations and an extensive tuning of hyperparameters. Given the defined constraints, it gives us more practical solutions for public safety as it gives an enormous boost in performance. Table 3 shows the number of layers the pre-trained models use for prediction and classification.

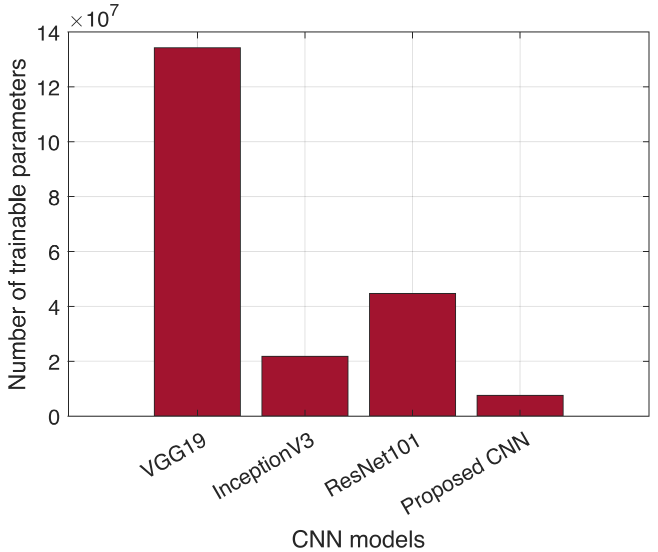

FIGURE 3 Number of trainable parameters for different models.

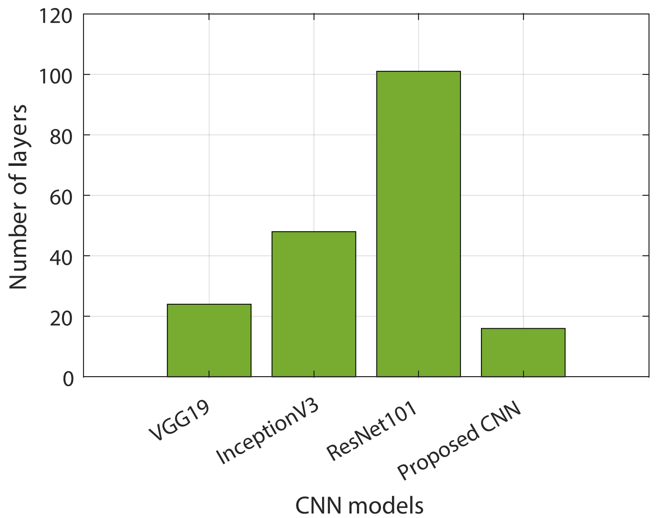

FIGURE 4 Number of layers for different models.

TABLE 3 Comparison of other pre-trained models with our model based on computational space required.

Model name	VGG19	InceptionV3	ResNet101	Proposed model
No. of trained parameters	134,268,738	21,776,548	44,654,504	7,483,910
No. of layers	24	48	101	16

4.2.4 | Model development

The proposed CNN model Ψ is made upon 16-layer architecture and combines various permutations and combinations of different activation functions, initializers, and regularizers with an additional max-pool layer. Figure 5 shows the architecture and layer-wise dissection of the entire proposed framework. The model comprises four convolutional layers, four max-pooling layers, three dense layers, three dropout layers, and an output layer, as shown in the figure. The proposed architecture is the sequence of convolution layers followed by dense neural layers, the input tensor of size

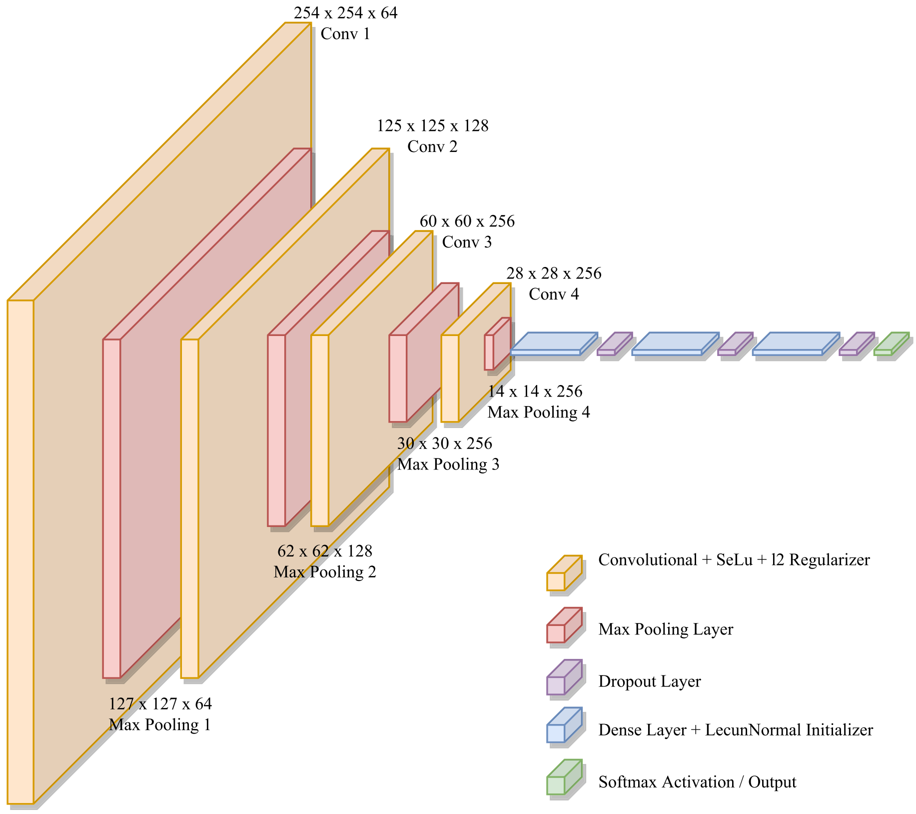

FIGURE 5 Proposed CNN model architecture.

255×255, first transferred through the convolutional block with 32 filters to extract features from the raw input. The convolution layer is paralleled with *L*2 regularizers to reduce the predictive model's variance, thus decreasing the influence of minor and unwanted variables. The subsequent *Max-Pooling* layer of size 2×2 reduces the complexity of extracted features by selecting the maximum value of the identified features and passing the tensor further of output shape $127 \times 127 \times 32$ through the architecture further with the convolutional layers of filter size 128 and 256, respectively. All convolution layers are comprised of *SeLU* activation function, which enables the model to actively consider negative values of the tensors and compute the feature values using the condition of *scaledexponential* that responds to both negative and positive values in an unbiased way. The performed convolution over the images works as follows.

$$\mu = \frac{N_x + 2P - N_h}{d} + 1. \tag{16}$$

Equation (16) represents the generation of output for the next layer from one layer to another. Here, μ represents the size of the output, N_x represents the size of the input, P represents the padding, N_h depicts the size of the filter, and d represents the stride. The regularization loss is performed over the convolution as follows:

$$\Gamma(W) = \frac{\alpha}{2}||W||_2^2 + \Gamma(W) \tag{17}$$

$$= \frac{\alpha}{2}\sum\sum \underset{i_j}{\overset{2}{w}} + \Gamma(W). \tag{18}$$

Equation (16) shows the output after applying the convolution kernel filter on the input image. This reduces the size of the input image and extracts the essential features for the convolutional model to train upon. This equation is essential for reducing the image's size and toning down the image into the most significant features.

This procedure is repeated for subsequent layers. After the series of convolution blocks, the flattened layer is introduced, which converts 3D tensors to 1D tensors with a size of 255. This can be fed further to the three dense layers of the neural network with a dimension of (128,256), (256,256), and (256,6), respectively, with *SeLU* and *Softmax* activation functions. These dense layers help select suitable features for enhancing the model's classification. After successfully passing through the convolution layers, the extracted features are allowed to go through the neural network for distributing the weights of the linear model, which is used for making predictions. Algorithm 1 describes the procedure of updating weights in the convolutional layer of the proposed CNN model.

Algorithm 1 Algorithm for updating weights in the convolutional layer.

```
procedure UPDATING WEIGHTS IN CNN(W, b)
    for i ← 1 to m do
        temp ← 0
        for j ← 1 to n do
            change ← 0
            change ← W[i][j] · X[j] + B[j]
            temp ← temp ± change
        end for
        Y[i] ← temp
    end for
end procedure
```

4.2.5 | CNN predictions

After model development, the model is ready to be deployed for use. The model predicts and categorizes the person in the image as criminal or not criminal. The CNN model classifies the image into one of the 6 classes based on the objects the image contains. This is done using the last dense layer where $Softmaxactivationfunction$, $\sigma(z)$ is used in multinomial logistic regression. It transforms a vector of K real numbers into a probability distribution with K alternative outcomes. As for our case, a list containing six elements would be the output, and the index number of the element with the highest value represents the object prediction for that image. The below equation represents the softmax activation function used in the proposed CNN model.

$$\sigma(z)_i = \frac{e^{z_i}}{\Sigma_{j=1}^{J} e^{z_j}}, \tag{19}$$

where each z_i value is one of the input vector's components and can take any real value. The normalization term at the bottom of the calculation guarantees that all of the function's output values will total 1, creating a proper probability distribution.

4.3 | Application layer

Once UAVs send the captured images back to the model and predictions are made, the application layer is pressed into service. The main functionality of the application layer is to alert the nearest public safety aiding agencies or departments of the criminal activities captured by drones. This enables agencies to act immediately and defend civilians against crimes, protecting public safety.

Another functionality of the application layer is that, regardless of the predictions made, the new images on which predictions are made are added to the data. This provides continuous data updating, enabling high model optimization, as the data would continue to increase, and the model would continuously be optimized with more images. This creates an improved model (the proposed model) and serves better with time and increased data.

5 | RESULTS AND DISCUSSIONS

5.1 | Experimental setup and simulation parameters

The work on the proposed framework is carried out on a cloud-based IDE, Google Collaboratory, on the scripting language Python. Several functionalities and APIs from various libraries are used to develop the framework. Two important functionalities of the TensorFlow library in use are *tf.Keras.regularizers.L2* and *tf.Keras.initializers.LecunNormal*. *tf.Keras.regularizers.l2* is used to tone down the overfitting which initially occurred during model building and *tf.Keras.initializers.LecunNormal* ensures that the model has high accuracy and performance while training weights. Other libraries used are *os*, *numpy*, *cv2*, and *plotly.express*.

CNN is a class of artificial neural networks that have emerged to be useful in various real-world applications. Using a variety of building pieces, including convolution layers, pooling layers, and fully connected layers, CNN is intended to automatically and adaptively learn spatial hierarchies of features through back-propagation. The application based on this paper is allied to image processing and identification. CNN is used for feature extraction from colored 3D images. The subsequent sections highlight the use of our CNN model and its behavior using different performance parameters like accuracy, loss, precision, and performance under different optimizers.

5.2 | Performance analysis

5.2.1 | Loss and validation loss

Figure 6 shows the loss versus validation loss graph while training our model. Here, the x-axis shows the number of epochs the model has been trained for, while the y-axis represents the loss. As shown in Figure 6, the loss and validation loss curves decrease with the increase in epochs. After extensive training of the framework, the loss and validation loss plot lines converge well after epoch number 10, which indicates less overfitting and a robust model.

The model is trained for 15 epochs; increasing the epochs causes overfitting and results in the divergence of loss and validation loss. Hence, an ideal number of epochs for training is chosen. During the training of the proposed CNN

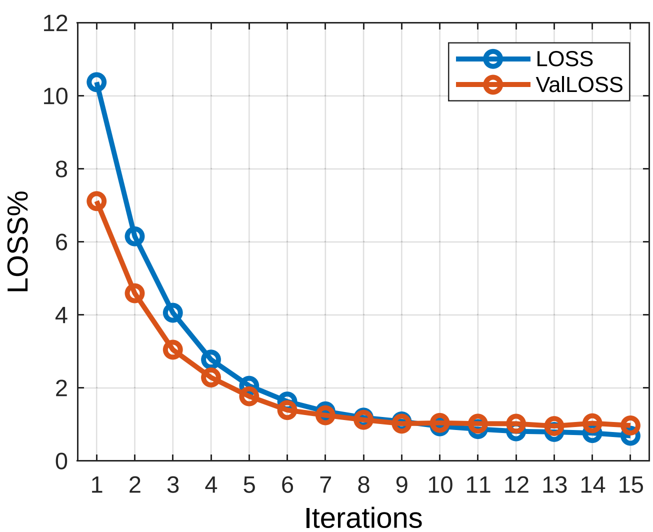

FIGURE 6 Loss versus validation loss curve while training the proposed model.

model, we can successfully tone down the loss substantially. Many methods to avoid overfitting are used during development, such as data augmentation, regularization, batch normalization, and adding dropout layers. Data augmentation is used in the initial stages of prepossessing the images; we resized the images and added many filters to them to optimally highlight the object to be detected. During training, regularization is used to help ignore the undue biases in the data and make an efficient model. We used l2 regularizers that followed ridge regression and added an l2 penalty equal to the square of the magnitude of the coefficient. l1 regularizer was not used as the penalty term; it adds the magnitude of the coefficient, which couldn't minimize the validation loss optimally.

5.2.2 | Accuracy and validation accuracy

Figure 7 shows the accuracy versus validation accuracy graph while training our model. Here, the x-axis shows the number of epochs the model has been trained for, whereas the y-axis represents the measure of accuracy. As shown in Figure 7, the accuracy and validation accuracy are increasing in value with increased epochs. After extensive training of the framework, the proposed model developed a training accuracy of around 84% and validation accuracy of 80%, which indicates less overfitting and a robust model. During the training of the proposed CNN model, various permutations of initializers and activation functions were used to maximize the accuracy such that the selected set of initializers serves their purpose of effectively increasing accuracy in an ideal way considering the chosen activation function, which performs best among all in use. The initializer used is *leCunNormal* along with *SELU* activation function to perfectly tone the values of weights and give a better start to the training process. Increasing the number of epochs results in overfitting, where the accuracy and validation accuracy curves diverge; hence, an ideal number of epochs is chosen for the model's training.

Figure 8 shows the comparison of accuracy versus validation accuracy for the different number of epochs training our model. Here, the x-axis shows the number of epochs the model has been trained for, whereas the y-axis represents the measure of accuracy. As shown in Figure 8, the accuracy and the validation accuracy continue to rise and converge with training; this indicates good extensive training of the proposed model. This stops after epoch number 15, after which the accuracy continues to increase, but the validation accuracy stagnates at around 75% while the training accuracy continues to increase up to epoch number 20; this indicates overfitting. Due to less number of data points as inputs for training, the model had to be trained upon a limited number of batches to classify multiple classes; thus, after several epochs, the model starts taking the previous inputs for retraining itself and thus occurs overfitting at a larger number of epochs. Overfitting is highly undesirable in the model as it would lead to false predictions; hence, the authors chose the ideal number of epochs for the model's training to be 15. Weight updating is understood to be the best for 15 epochs.

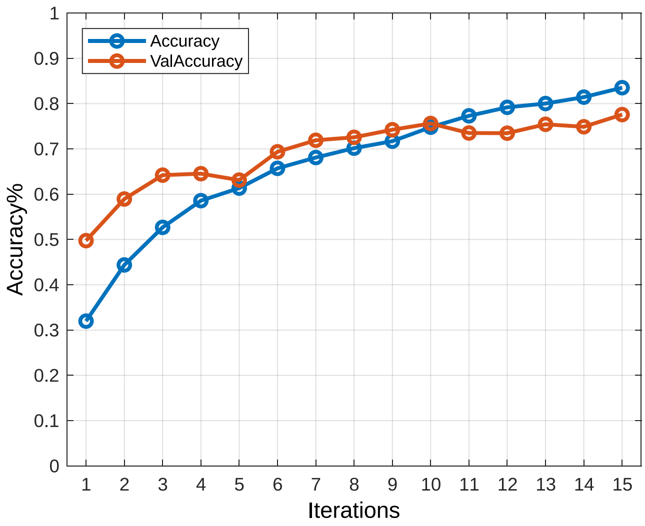

FIGURE 7 Accuracy versus validation accuracy curve while training the proposed model.

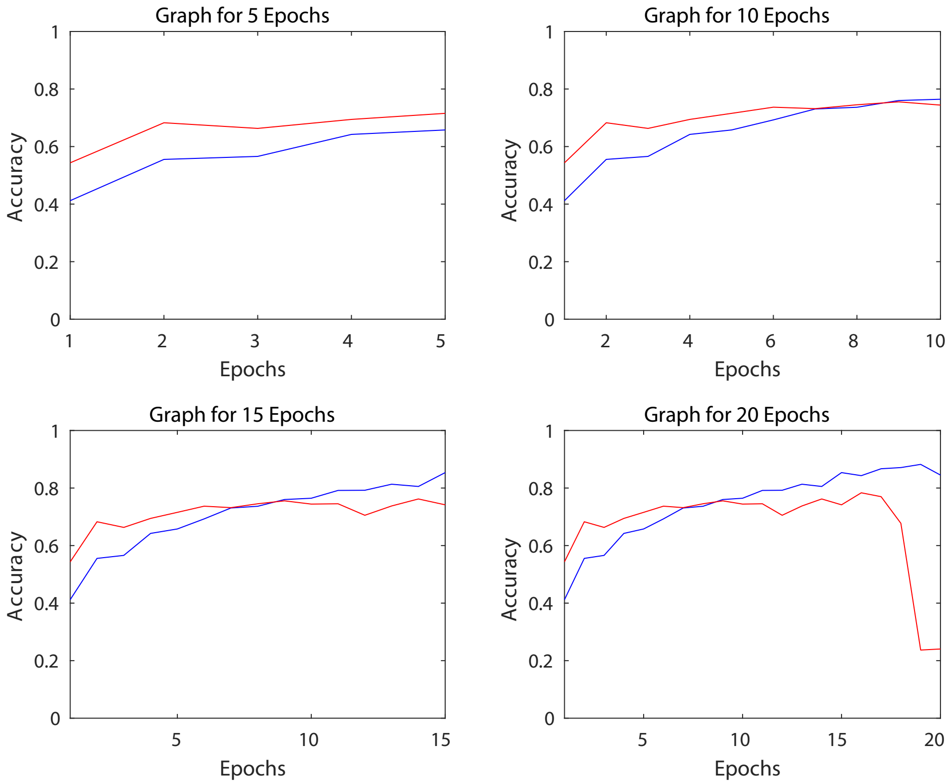

FIGURE 8 Comparison of training and validation accuracy during training of the proposed model over a different number of epochs. The red line indicates validation accuracy, and the blue line indicates training accuracy.

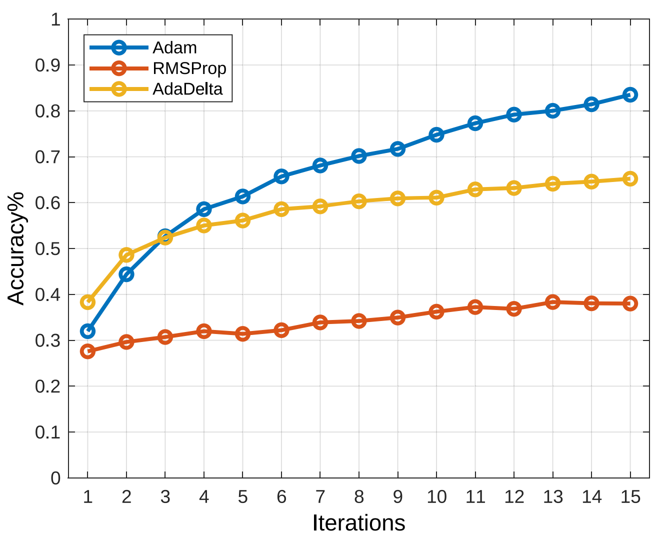

FIGURE 9 Comparison of accuracies using different optimizers while training the proposed model.

5.2.3 | Performance under different optimizers

Figures 9 and 10 show the training accuracy curve under different optimizers while training our model and the training loss curve under different optimizers while training our model. In Figure 9, the *x*-axis shows the number of epochs the model has been trained for, whereas the *y*-axis represents the measure of accuracy. In Figure 10, the *x*-axis shows the number of epochs the model has been trained for, whereas the *y*-axis represents the loss. The different colored curves

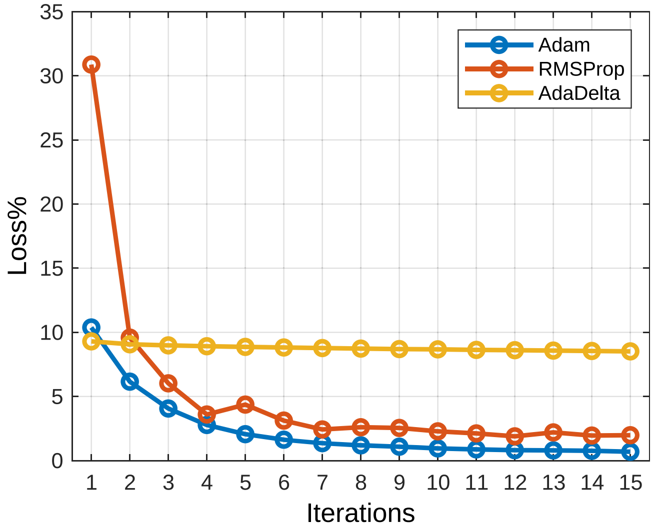

FIGURE 10 Comparison of losses using different optimizers while training the proposed model.

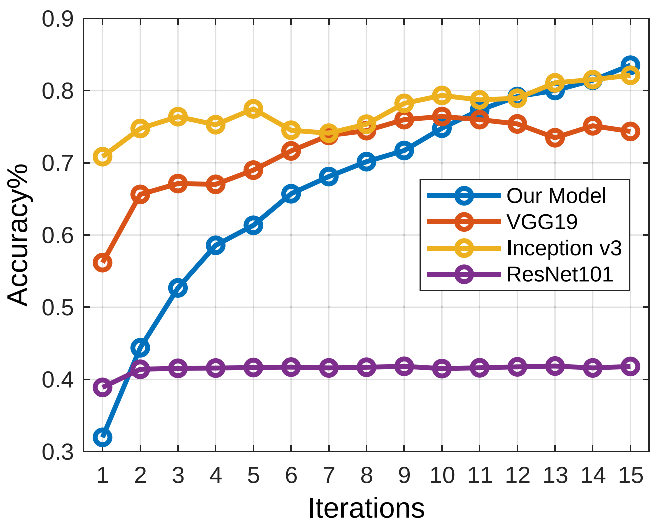

FIGURE 11 Comparison of accuracies of the proposed model with other pre-trained models.

are accuracy curves for different optimizers. The different optimizers in use are Adam, RMSprop, and AdaDelta. As shown in Figures 9 and 10, the optimizer that gives the highest accuracy and minimal loss is Adam.

Adam is an extended version of SGD and can be used in places where SGD is used to update values of parameters optimally. Adam creates an optimization technique that can handle sparse gradients in noisy situations by combining the best features of the AdaGrad and RMSProp algorithms. For example, the second moment with a decay rate to speed up from AdaGrad is used by RMSprop, whereas, in Adam, both the first and second moments are used, making Adam the superior option. AdaDelta and Adam are similar algorithms, except that AdaDelta uses the RMS of parameter updates in the numerator update rule. On the other hand, Adam inculcates bias correction and momentum to RMSprop. Our dataset includes images of low resolution, making Adam perform well than any other optimizer.

5.2.4 | Comparison between different pre-trained models and our model

Figure 11 shows the comparison of accuracy given by our model with other pre-trained models. In Figure 11, the *x*-axis shows the number of epochs the model has been trained for, whereas the *y*-axis represents the accuracy value. Different pre-trained models used for comparison with our model are VGG19, InceptionV3, and ResNet101. Figure 11 shows that the proposed model gives better accuracy than any other pre-trained models.

The other models are trained on the ImageNet dataset, whereas our model is trained on the SOHAs weapon detection dataset. The ImageNet dataset is a very extensive dataset compromising many different objects; conversely, the SOHAs weapon detection dataset emphasizes object categorization into dangerous and non-dangerous categories. Due to this, the other models cannot categorize dangerous and non-dangerous objects as efficiently as the proposed model.

6 | CONCLUSION

In this paper, we have presented a framework for identifying handheld objects and determining whether they threaten public safety. The proposed framework uses multiple UAVs for image collection and a CNN model based on DL to identify crime-related weapons and classify individuals as criminals or non-criminals. Our CNN model has been developed with high prediction accuracy and fewer computational resources than other pre-trained models, achieving an impressive accuracy of 0.8352 and a validation accuracy of 0.7758. Our model outperforms other pre-trained models, such as VGG19, Inception V3, and Resnet101, regarding accuracy, loss, number of trainable parameters, and number of layers in the CNN architecture. Moreover, our proposed framework has been designed to operate with the lowest cost and complexity possible, making it a superior option compared to other pre-trained models.

In the future, we will improvise the performance of the proposed framework by incorporating a blockchain network to confront data manipulation attacks on crime data. We also plan to perform a case study on the real-time performance of the model and improve its efficiency by implementing decentralization.

CONFLICT OF INTEREST STATEMENT

Authors declare that there is no financial or non-financial interests that are directly or indirectly related to the work submitted for publication to this Journal.

DATA AVAILABILITY STATEMENT

No data used to carry out this research.

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