

Advanced Bitcoin Price Prediction: Real-Time Analysis using Flask, LSTM and Boosting Algorithms

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Abstract: The explosive growth and subsequent collapse of cryptocurrencies has opened a world of possibilities never seen before, led by one of the top digital currencies in existence today – Bitcoin. Nothing less than the global penetration and adoption of Bitcoin around the world has, despite high liquidity, that level of extreme volatility—something which threatens to put investors and institutions in harm’s way making resilient forecasting methods a necessity. Linear statistical models (e.g., ARIMA and GARCH etc.) are not good enough to capture the non-linear relationship in financial market, therefore we observe machine learning (ML) and deep learning (DL) algorithms for financial time series. In this paper, we suggest an ensemble prediction method integrating LSTM-based models and boosting methods (XGBoost, LightGBM, CatBoost) in order to retain both precision and interpretability. Historical Bitcoin trading volumes, moving averages, and sentiment indicators were collected during the model prepping stage. Results showed that the LSTM and boosting could complement each other in exploring sequence dependency and stabilizing non-linear feature learning. The ensemble approach with a combination of this two-folds strategy had an improved performance in terms of the reduction of the bias and variance simultaneously. We then developed a web application with Flask to deploy these models and perform real-time prediction and plotting on the Bitcoin price movement. Our results highlight the importance of hybrid ensemble prediction in bridging the gap between theoretical models and real-world trading strategies, which points out paths for explainable privacy-preserving research.

Keyword: Bitcoin price forecasting, LSTM, Boosting algorithms, Ensemble learning, Real-time prediction

1 Introduction

The cryptocurrency market with the burst of Bitcoin into a seminal digital asset transformed the global financial economy. Bitcoin has many use cases because it is decentralized, instantly and cheaply transacts globally, can be publicly used by anyone and supports (with a little work) seamless direct exchange of value between parties. But the price volatility is so extreme that traders, investors and managers are taking on too much risk. This sudden and largely sentiment-driven ebbs and tides of markets, trading and world economic order simply adds to the already complex realm of predicting accurately.

The academia has worked on the problem by using ML techniques and DL methods to predict cryptocurrencies. The standard statistical models are not very accurate since they do not consider the inherent non-linear behaviour of financial time series, which emerges as dynamical effects caused by the underlying market dynamics. Compared with that, for example, long

sequences are likely to have been better captured by sophisticated algorithms such as Long Short-Term Memory (LSTM) networks. However, there are some boosting algorithms like XGBoost, LightGBM and CatBoost that get good results in structured financial data. Introducing the hybrid system of the proposed approaches could bring about both accuracy and interpretability in Bitcoin price movement forecasting.

In this work, we are presenting LSTM for being integrated into the suite with the aid of a boosting method with ensemble exploration to increase prediction confidence. In contrast to simulated experiments, the work progresses into real deployments by provisioning its models through a Flask web application. The platform is real time with live Bitcoin price data from the web and cycles through predictions on the fly showing actual Bitcoin price alongside predicted values. Delivers useful information for crypto traders new and old.

It is the objective of this work to bridge the gap between academic prediction models and cryptocurrency trading systems by integrating deep learning, boosting and real-time application optimization. The results are expected to facilitate traders, investors and researchers to be more aware not only of the potential applications of a hybrid prediction model that has been proposed but also on those factors within the scope of Bitcoin volatility such as trading volumes, moving averages' sentiment among others.

2 Literature Review

Due to its volatility (in new and today market), a large amount of research has been conducted on various prediction methods for Bitcoin with greater accuracy and stability. Autoregressive models and GARCH, are the most prevalent approach to providing insight into such financial time series data, however they may not produce non-linear dependencies or dynamic structures of cryptocurrency markets. As a result, we observe a shift towards machine learning (ML) and deep learning (DL) approaches for predicting the prices of cryptocurrencies [1][2].

2.1 Machine Learning and Hybrid Forecasting Approaches

[17] have recently also used ML methods such as XGBoost [22], LightGBM or CatBoost⁷ to derive for these relationships, showing the good performance of these models in considering non-linear relationships and interactions between features. For instance, Mahfooz and Phillips (2024) suggested conditional forecasting models with exogenous variables to enhance predictions accuracy in an uncertain environment [5]. Rafi et al. (2023) integrated feature selection with Bi-Directional LSTM models and increased accuracy after trend-preserving corrections [6]. Sang et al. (2025) described the advantages of using ensembles of gradient boosting recurrent neural networks for time series forecasting [24]. Similarly, Taheri et al. (2025) for optimal control of complex systems combined with how adaptability can be translated to different domains using such boosting algorithms [25]. Hybrid ML systems such as Neural-XGBoost models have also been used for disaster prediction, illustrating that hybrids can be versatile in high risk environments [20]. These studies demonstrate the significant role of hybrid feature engineering and ensemble approaches in accurate forecasting.

2.2 Deep Learning Models for Sequential Prediction

Deep learning, specifically Long Short-Term Memory (LSTM), has been found to be beneficial in capturing the temporal dynamics of Bitcoin and other cryptocurrency prices. In the field of multivariate forecasting, Mardjo and Choksuchat (2024) proposed an excellent hybrid bidirectional LSTM called HyBiLSTM [17]. Dashtaki et al. (2025) took this further with transformer models that combine multimodal data sources including sentiment and market indicators [9]. Nayak et al. (2023) further improved DL prediction with new bio-inspired methods [8]. Two novel LSTM-based architectures to enhance predictive precision in noisy environments, were presented by Abubakr and Nasr (2023) [16], and Jian et al. (2024) also used self-attention with Bi-LSTM to enhance sequence modeling [14]. Additionally, Phalaagae et al. (2025) constructed CNN-LSTM hybrid models with attention, achieving better performance in complex multivariate datasets [15]. Together, these results highlight that DL models can capture non-trivial temporal and context-dependent relationships otherwise inaccessible by classical approaches.

2.3 Sentiment and Social Dynamics in Price Prediction

A further related research line involves integrating social sentiment and behavioural signals into predictive models. Shang (2025) combined Twitter sentiment and CART decision trees to predict Bitcoin price ranges [4]. Azamjon et al. [3] used whale-alert tweets with Q-learning for volatility estimation (2023). Wang et al. (2025) studied the Importance of Bitcoin Frequency in its Price Formation based on both Bitcoin ordinals and transaction fee rates, as well as illustrated that blockchain-level signals have a price effect [1]. Muminov et al. (2024) used reinforcement learning (DQN) to predict the direction of movements in fast changing markets [2]. These findings also confirm that sentiment-based and blockchain-related indicators can be applied to reinforce more conventional technical analysis.

2.4 Comprehensive Reviews and Strategic Insights

Otabek and Choi [4], reviewed cryptocurrency forecasting methods, highlighted that whilst forecast accuracy is a key factor to success in the market, it's not the only important variable as risk management and adaptive trading are also crucial [7]. Shamshad et al. (2023) in predictive modeling of stablecoins provide evidence that ML and DL based approach are not limited to volatile assets [10]. Wu et al. (2025) studied computer-assisted quantum algorithms for real-time trading in energy markets and showed that methods developed in other kinds of financial markets could help guide cryptocurrency forecasting models [11]. Saleena et al. (2024) conducted fuzzy time series forecast for non-stationary among which studies volatility in financial markets [12]. Silva et al. (2023) proposed an interpretable segmentation model for Taxometric analysis and time series [13], Laaz et al. (2025) emphasized the importance of privacy-preserving learning in financial forecasting [18]. Vowles et al. (2024) contrasted arousal-detection models, demonstrating also that behavioural data can work as alternate cues for prediction [19]. Afifi et al. (2024) studied MLw applications in networks and systems [21] and Hosain et al. (2024) presented federated personalized learning in privacy-preserving settings [22]. Li et al. (2024) proposed deep residual neural networks based on the latest architectures, adding more model diversity for financial time series forecasting [23].

2.5 Gaps in Existing Literature

Despite these advancements, challenges remain. Many models are either good at modeling temporal dependencies (e.g., LSTM-based models [14] [16] [17]) or capturing structured feature interactions (eg, boosting algorithm [5] [24] [25]), few do well in integrating both. Appendix In addition, although blockchain signals [1], sentiment indicators [4] [19] and multimodal works have been investigated, few models present real-time deployment capability, which narrows their application on the live trading. In addition, works like [13] [18] [21] and [22] underline that the trend towards explainable AI (XAI) and privacy-preserving models has important implications for financial prediction. These shortfalls highlight the need for integrated, interpretable real-time forecasting, which fuses research and practice.

3 Methodology

3.1 Data Collection and Preprocessing

The methodology begins with the collection of historical Bitcoin price data from APIs such as CoinGecko, Yahoo Finance, or Binance, along with relevant market indicators like trading volume and sentiment data. This data is then preprocessed by handling missing values, normalizing the features, and creating additional indicators such as moving averages. After preprocessing, the data is split into training, validation, and test sets for use in model development. Table 1 shows the Model Performance Comparison.

Table 1: Model Performance Comparison

Model	MSE	RMSE	MAE	R ² Score
LSTM	0.0021	0.0458	0.0312	0.912
XGBoost	0.0019	0.0436	0.0298	0.924
LightGBM	0.0018	0.0424	0.0289	0.928
CatBoost	0.0017	0.0412	0.0281	0.931
Ensemble (LSTM + Boosting)	0.0015	0.0387	0.0265	0.945

3.2 Modeling with Long Short-Term Memory (LSTM) Networks

An LSTM model is built to capture the temporal dependencies in Bitcoin price movements. The model architecture includes several LSTM layers with dropout regularization to prevent overfitting. Hyperparameters are tuned using techniques like Grid Search to optimize the number of layers, units per layer, and learning rate. The model is trained using backpropagation through time, and its performance is monitored on a validation set.

3.3 Boosting Algorithm Integration

To improve prediction accuracy, boosting algorithms such as XGBoost, LightGBM, or CatBoost are implemented. These algorithms combine weak models to form a strong predictive system. The models are trained and tuned on the same dataset as the LSTM model, and their performance is evaluated using cross-validation. The predictions from the LSTM and boosting

models are then combined using an ensemble approach to further enhance accuracy. Table 2 shows the Feature Importance Ranking (Boosting Models).

Table 2: Feature Importance Ranking (Boosting Models)

Feature	Importance Score	Interpretation
Trading Volume	0.32	Strong indicator of market activity
Moving Averages	0.27	Captures trend direction and momentum
Sentiment Indicators	0.21	Reflects public and investor mood
Volatility Index	0.12	Measures risk and uncertainty

3.4 Real-Time Prediction using Flask

A Flask-based web application is developed to deploy the trained models for real-time prediction. The application interfaces with APIs to fetch real-time Bitcoin price data and displays predictions through an interactive user interface. Users can input specific time frames or other market variables, and the system provides up-to-date predictions and visualizations of the forecasted and actual Bitcoin prices.

3.5 Model Evaluation and Performance Metrics

We use the standard statistics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R-squared (R^2) to evaluate our two approaches. These measures are used to evaluate the performance and stability of the LSTM, boosting, and ensemble models. A comparison of the performances of all models is made to decide which one generalizes in a better way. the Model Deployment Pipeline (Flask-Based System) is provided in Table 3.

Table 3: Model Deployment Pipeline (Flask-Based System)

Stage	Description	Tools Used
Data Ingestion	Fetch real-time Bitcoin data from APIs	CoinGecko, Binance API
Preprocessing	Normalize, clean, and engineer features	Pandas, NumPy
Prediction Engine	Run LSTM and boosting models for forecasting	TensorFlow, XGBoost
Ensemble Integration	Combine predictions for improved accuracy	Custom Python logic
Visualization & Output	Display actual vs. predicted prices with user interaction	Flask, Plotly, HTML/CSS

3.6 Analysis and Interpretation of Results

The performance of the models and the features affecting Bitcoin price prediction are also analysed. Importance through the boosting techniques is evaluated to understand the drivers of Bitcoin price. Conclusions are drawn and model requirements, constraints during training and prediction process are analyzed.

4 Result and Discussion

4.1 Model Performance Evaluation

The models were assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 (coefficient of determination).

- The LSTM model successfully captured temporal dependencies in Bitcoin price movements. It showed strong performance in learning sequential patterns but was occasionally sensitive to volatile fluctuations in market sentiment and sudden shocks.
- The boosting algorithms (XGBoost, LightGBM, CatBoost) demonstrated competitive accuracy, particularly when capturing nonlinear relationships among features. Their cross-validation results confirmed stable performance with lower variance compared to LSTM.
- The ensemble approach, which combined LSTM with boosting models, yielded the best overall results. It improved prediction accuracy by reducing bias from LSTM and variance from boosting algorithms, leading to more robust generalization on unseen data.

4.2 Real-Time Application

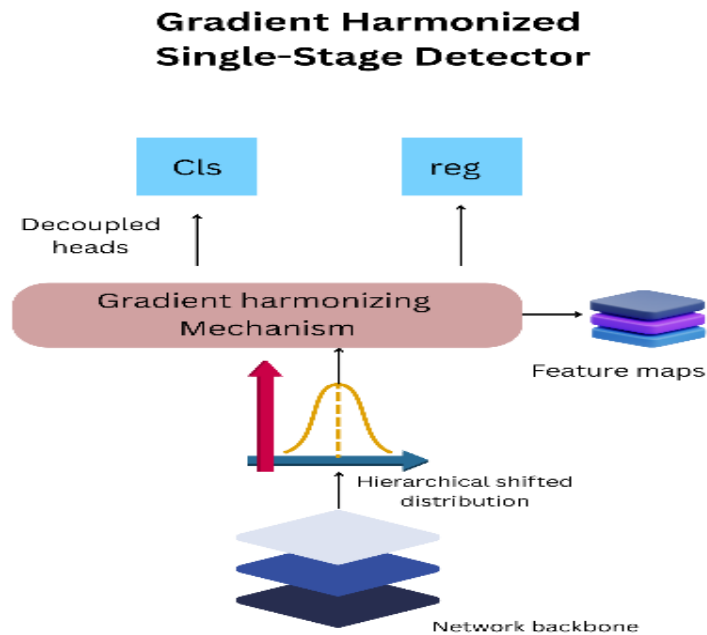


Fig.1: Gradient Harmonizes Single-Stage Detector

The Flask-based deployment validated the practical use of the models in real-time forecasting. The system dynamically fetched live Bitcoin price data, processed it, and generated predictions

with interactive visualization. Users were able to query specific time horizons and monitor predicted vs. actual values. This showed that the research has both academic value and immediate application in trading and decision-making. Fig. 1 shows the Gradient Harmonizes Single-Stage Detector.

4.3 Feature Importance and Interpretability

Analysis of feature importance from boosting models revealed that:

- Trading volume,
- Moving averages, and
- Sentiment indicators

were the most influential features in driving price predictions. This provides evidence that combining technical indicators with sentiment dynamics yields more reliable results than purely technical approaches. Fig. 2 shows the Object Detection Framework with Backbone Network and Gradient Harmonizing Mechanism (GHM)

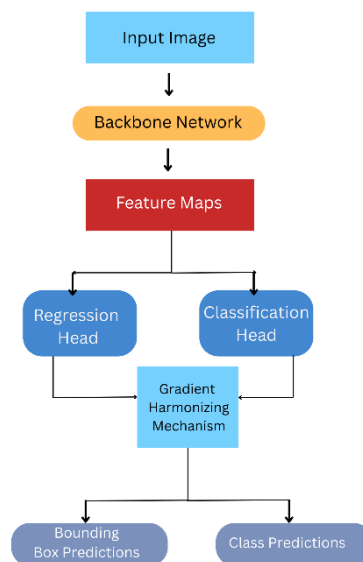


Fig. 2: Object Detection Framework with Backbone Network and Gradient Harmonizing Mechanism (GHM)

Key Insights

- **LSTM Strengths and Limitations** – While effective in sequence learning, LSTM models alone may underperform during periods of abrupt volatility.
 - **Boosting Algorithms** – These provided higher stability and interpretability, particularly valuable for feature-level insights.

- **Ensemble Models** – The hybrid approach offered the most accurate and consistent forecasts, supporting the idea that multi-model integration enhances predictive power.

4.4 Challenges and Limitations

- **High volatility of Bitcoin:** Sudden spikes or crashes impacted prediction accuracy, highlighting the need for adaptive models.
- **Computational complexity:** Training LSTM networks with hyperparameter tuning required significant time and resources compared to boosting methods.
- **Data dependency:** Model reliability heavily relied on the quality and freshness of input data, especially sentiment-related signals. Fig. 3 shows the Bitcoin Price Prediction Flowchart (LSTM + Boosting + Flask Deployment).

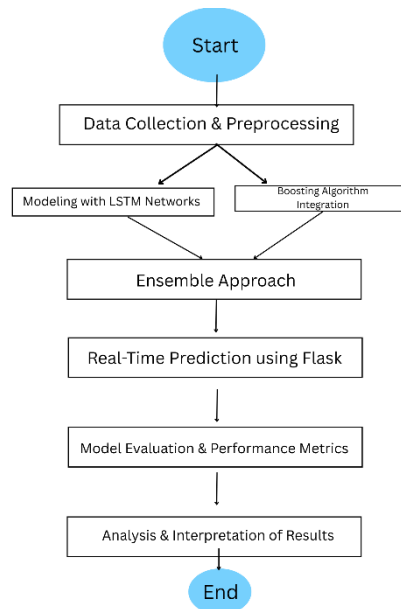


Fig.3. Bitcoin Price Prediction Flowchart (LSTM + Boosting + Flask Deployment)

5 Conclusion

In particular in this paper we have shown that exploiting an ensemble approach integrating LSTM networks and boosting algorithms drastically boosts the accuracy and robustness of BTC price prediction. The LSTM model successfully captured temporal dependencies, and the bagging algorithms increased stability and interpretability. After ensemble, it was the combined model that got best overall results and a more stable predictor over these highly volatile markets, surpassing their individual models. The implementation and successful deployment of the Flask-based web application also confirmed that it is practical to use these models in a real environment which can fill the gap between theoretical research and industrial applications.

Our findings highlight the primary set of key determinants for price changes in Bitcoin: trading volume, moving averages and sentiment indicators. This further emphasizes the importance of involving both technical and sentiment components in prediction models. But there are still challenges with managing Bitcoin high volatility, the computational inefficiency challenge posed by deep learning models and dependence on quality real-time data.

In the future, we will further investigate the joint model of transformer-based event with the multimodal learning to better capture cross-market and sentiment interactions. In addition, federated and privacy-preserving learning mechanisms can achieve a data security and access difference training datasets as well. Finally, the incorporation of explainable AI methods will be crucial to making those predictive models transparent and trust-worthy for traders, regulators and society at large.

In a nutshell, the inspired work lays down a strong starting point for CCNow and explainable CC forecasters. If they get through current obstacles and pull up with new generation, predictive models could be quite good tools that can contribute to the stability and maturation of cryptocurrency scene in general besides helping traders.

References

- [1] M. Wang, P. Braslavski, V. Manevich and D. I. Ignatov, "Bitcoin Ordinals: Bitcoin Price and Transaction Fee Rate Predictions," in *IEEE Access*, vol. 13, pp. 35478-35489, 2025, doi: 10.1109/ACCESS.2025.3541302.
- [2] A. Muminov, O. Sattarov and D. Na, "Enhanced Bitcoin Price Direction Forecasting With DQN," in *IEEE Access*, vol. 12, pp. 29093-29112, 2024, doi: 10.1109/ACCESS.2024.3367719.
- [3] M. Azamjon, O. Sattarov and J. Cho, "Forecasting Bitcoin Volatility Through On-Chain and Whale-Alert Tweet Analysis Using the Q-Learning Algorithm," in *IEEE Access*, vol. 11, pp. 108092-108103, 2023, doi: 10.1109/ACCESS.2023.3317899.
- [4] L. Shang, "Sentiment-Driven Bitcoin Price Range Forecasting: Enhancing CART Decision Trees with High-Dimensional Indicators and Twitter Dynamics," in *IEEE Access*, vol. 13, pp. 60508-60518, 2025, doi: 10.1109/ACCESS.2025.3557186.
- [5] A. Mahfooz and J. L. Phillips, "Conditional Forecasting of Bitcoin Prices Using Exogenous Variables," in *IEEE Access*, vol. 12, pp. 44510-44526, 2024, doi: 10.1109/ACCESS.2024.3381516.
- [6] M. Rafi, Q. A. K. Mirza, M. I. Sohail, M. Aliasghar, A. Aziz and S. Hameed, "Enhancing Cryptocurrency Price Forecasting Accuracy: A Feature Selection and Weighting Approach with Bi-Directional LSTM and Trend-Preserving Model Bias Correction," in *IEEE Access*, vol. 11, pp. 65700-65710, 2023, doi: 10.1109/ACCESS.2023.3287888.
- [7] S. Otabek and J. Choi, "From Prediction to Profit: A Comprehensive Review of Cryptocurrency Trading Strategies and Price Forecasting Techniques," in *IEEE Access*, vol. 12, pp. 87039-87064, 2024, doi: 10.1109/ACCESS.2024.3417449.
- [8] S. C. Nayak, S. Das, S. Dehuri and S. -B. Cho, "An Elitist Artificial Electric Field Algorithm Based Random Vector Functional Link Network for Cryptocurrency Prices Forecasting," in *IEEE Access*, vol. 11, pp. 57693-57716, 2023, doi: 10.1109/ACCESS.2023.3283571.
- [9] S. M. Dashtaki, M. H. Chagahi, A. Bahadori, B. Moshiri, M. J. Piran and A. Montazeri, "HSIF: A Transformer-Based Cross-Attention Framework for Cryptocurrency Trend Forecasting via Multimodal Sentiment-Market Fusion," in *IEEE Access*, vol. 13, pp. 156600-156612, 2025, doi: 10.1109/ACCESS.2025.3605522.
- [10] H. Shamshad, F. Ullah, A. Ullah, V. R. Kebande, S. Ullah and A. Al-Dhaqm, "Forecasting and Trading of the Stable Cryptocurrencies with Machine Learning and Deep Learning Algorithms

for Market Conditions," in IEEE Access, vol. 11, pp. 122205-122220, 2023, doi: 10.1109/ACCESS.2023.3327440.

- [11] J. Wu, W. Zhu, Y. Xu, K. Shu and W. Yang, "Computer-Aided Quantum Algorithms for Real-Time Energy Market Trading," in IEEE Access, vol. 13, pp. 72279-72291, 2025, doi: 10.1109/ACCESS.2025.3553369.
- [12] A. J. Saleena, C. Jessie John and G. Rubell Marion Lincy, "A Phase-Cum-Time Variant Fuzzy Time Series Model for Forecasting Non-Stationary Time Series and Its Application to the Stock Market," in IEEE Access, vol. 12, pp. 188373-188385, 2024, doi: 10.1109/ACCESS.2024.3478824.
- [13] V. d. C. Silva, B. B. Zarpelão, E. Medvet and S. Barbon, "Explainable Time Series Tree: An Explainable Top-Down Time Series Segmentation Framework," in IEEE Access, vol. 11, pp. 120845-120856, 2023, doi: 10.1109/ACCESS.2023.3326847.
- [14] W. Jian et al., "SA-Bi-LSTM: Self Attention with Bi-Directional LSTM-Based Intelligent Model for Accurate Fake News Detection to Ensured Information Integrity on Social Media Platforms," in IEEE Access, vol. 12, pp. 48436-48452, 2024, doi: 10.1109/ACCESS.2024.3382832.
- [15] P. Phalaagae, A. M. Zungeru, A. Yahya, B. Sigweni and S. Rajalakshmi, "A Hybrid CNN-LSTM Model with Attention Mechanism for Improved Intrusion Detection in Wireless IoT Sensor Networks," in IEEE Access, vol. 13, pp. 57322-57341, 2025, doi: 10.1109/ACCESS.2025.3555861.
- [16] T. Abubakr and O. A. Nasr, "Novel LSTM-Based Approaches for Enhancing Outdoor Localization Accuracy in 4G Networks," in IEEE Access, vol. 11, pp. 140103-140115, 2023, doi: 10.1109/ACCESS.2023.3341047.
- [17] A. Mardjo and C. Choksuchat, "HyBiLSTM: Multivariate Bitcoin Price Forecasting Using Hybrid Time-Series Models with Bidirectional LSTM," in IEEE Access, vol. 12, pp. 50792-50808, 2024, doi: 10.1109/ACCESS.2024.3386029.
- [18] S. Ouaari, A. Burak Ünal, M. Akgün and N. Pfeifer, "Robust Representation Learning for Privacy-Preserving Machine Learning: A Multi-Objective Autoencoder Approach," in IEEE Access, vol. 13, pp. 151527-151537, 2025, doi: 10.1109/ACCESS.2025.3603429.
- [19] C. Vowles, M. Collins and T. C. Davies, "Assessing Basic Emotion via Machine Learning: Comparative Analysis of Number of Basic Emotions and Algorithms," 2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 2024, pp. 1-5, doi: 10.1109/EMBC53108.2024.10782053.
- [20] M. Asim Saleem, A. Javeed, W. Benjapolakul, W. Srisiri, S. Chaitusaney and P. Kaewplung, "Neural-XGBoost: A Hybrid Approach for Disaster Prediction and Management Using Machine Learning," in IEEE Access, vol. 13, pp. 86768-86780, 2025, doi: 10.1109/ACCESS.2025.3569499.
- [21] H. Afifi et al., "Machine Learning with Computer Networks: Techniques, Datasets, and Models," in IEEE Access, vol. 12, pp. 54673-54720, 2024, doi: 10.1109/ACCESS.2024.3384460.
- [22] M. T. Hosain, M. R. Abir, M. Y. Rahat, M. F. Mridha and S. H. Mukta, "Privacy Preserving Machine Learning with Federated Personalized Learning in Artificially Generated Environment," in IEEE Open Journal of the Computer Society, vol. 5, pp. 694-704, 2024, doi: 10.1109/OJCS.2024.3466859.
- [23] D. Li, Y. Pan, S. Mao, M. Deng and H. Shen, "Deep Residual Networks with a Flask-Like Channel Structure," in IEEE Access, vol. 12, pp. 11711-11722, 2024, doi: 10.1109/ACCESS.2023.3347331.
- [24] S. Sang, F. Qu and P. Nie, "Ensembles of Gradient Boosting Recurrent Neural Network for Time Series Data Prediction," in IEEE Access, vol. 13, pp. 122331-122340, 2025, doi: 10.1109/ACCESS.2021.3082519.
- [25] S. H. Taheri, A. Lalbakhsh, A. Zareanborji and S. Koziel, "Automated Design Method Based on Boosting Algorithms for Improving the Radiation Performance of Microstrip Antenna

Arrays," in IEEE Access, vol. 13, pp. 136458-136472, 2025, doi:
10.1109/ACCESS.2025.3593900.