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Design of a Stock Market Prediction System Using Artificial Intelligence-Based Approaches

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***Abstract*—Stock market prediction is one of the most challenging problems in computational finance due to the dynamic, nonlinear, and stochastic nature of financial markets. Traditional statistical methods often fail to capture complex temporal dependencies and hidden market patterns. This paper proposes a hybrid artificial intelligence-based stock market prediction framework integrating deep learning, technical indicator analysis, and ensemble machine learning for improved forecasting accuracy. The proposed system combines Long Short-Term Memory (LSTM) networks for temporal sequence modeling, convolutional feature extraction for trend representation, and ensemble regression for adaptive prediction refinement. The framework incorporates market indicators including moving averages, Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and trading volume dynamics to improve predictive capability. Experimental evaluation is designed using benchmark financial datasets and multiple performance metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), prediction accuracy, and directional forecasting precision. The expected results indicate that the proposed hybrid framework can significantly improve forecasting reliability compared with standalone machine learning and statistical approaches. The proposed system contributes toward intelligent financial analytics, decision support, and AI-driven investment systems.**

***Index Terms*—Stock Market Prediction, Artificial Intelligence, Deep Learning, LSTM, Financial Forecasting, Machine Learning, Time-Series Analysis**

I. Introduction

Financial markets generate highly dynamic and nonlinear time-series data influenced by economic indicators, investor sentiment, geopolitical events, and market psychology. Accurate stock market prediction has therefore become an important research area in computational intelligence, quantitative finance, and decision-support systems.

Traditional forecasting methods such as autoregressive models, moving averages, and econometric techniques rely on linear assumptions and often fail to capture complex temporal dependencies. Recent advancements in artificial intelligence (AI) and deep learning have enabled the development of intelligent forecasting systems capable of learning hidden market structures and sequential trends directly from financial data.

Machine learning models such as Support Vector Regression (SVR), Random Forests, and Artificial Neural Networks (ANNs) have shown improved prediction capability compared with classical statistical techniques. More recently, Long Short-Term Memory (LSTM) networks and transformer-based architectures have demonstrated strong performance in modeling temporal dependencies within financial time-series data.

Despite these advances, existing stock prediction systems still face limitations related to market volatility, overfitting, noise sensitivity, and poor generalization under rapidly changing market conditions. Most systems rely either on standalone deep learning or isolated technical analysis without effectively integrating hybrid intelligence and adaptive ensemble learning.

This paper proposes a hybrid artificial intelligence-based stock market prediction framework integrating deep sequential learning, technical indicator modeling, and ensemble prediction refinement. The major contributions of this paper are summarized as follows:

- Development of a hybrid AI framework integrating LSTM, CNN feature extraction, and ensemble regression.
- Incorporation of technical indicators for improved market trend representation.
- Adaptive prediction refinement using ensemble learning.
- Comprehensive computational analysis using multiple financial forecasting metrics.
- Emphasis on intelligent financial decision-support systems.

II. Related Work

Recent advances in artificial intelligence and machine learning have significantly influenced financial forecasting and intelligent market analytics. Distributed AI frameworks such as FIR-Robot demonstrated efficient federated learning and collaborative information processing for resource-constrained environments [6], while fog-based adaptive task offloading strategies improved computational efficiency in intelligent systems [9]. These studies highlight the importance of scalable and low-latency AI architectures relevant to financial analytics platforms.

Semantic intelligence and ontology-driven deep learning have further improved contextual information processing. Singh *et al.* integrated ontology construction with semantic embeddings and deep neural models for intelligent retrieval systems [8], while hybrid semantic inference using ontology-guided embeddings was explored in [12]. Such semantic modeling approaches are valuable for financial forecasting, where contextual interpretation of market indicators and hidden relationships is critical.

Secure AI-driven systems have also gained importance in data-sensitive applications. Rakheja *et al.* proposed a hybrid encryption and biometric authentication framework for secure image transmission [7]. In parallel, lightweight real-time vision models optimized for low-resource environments demonstrated robust and efficient AI deployment [10]. Hybrid machine learning systems for recognition under degraded visual conditions were further investigated in [11]. These works collectively emphasize robustness, adaptability, and secure AI integration, which are equally important in intelligent financial prediction systems.

Hybrid machine learning has shown strong performance in behavioral and sequential analytics. Singh *et al.* developed a hybrid framework for Alzheimer's disease detection using behavioral data [14], while advancements in speech recognition and emotional intelligence for voice assistants were investigated in [16]. Enhanced NLP-based intelligent assistant systems were further explored in [17]. These studies reinforce the effectiveness of sequential learning and adaptive intelligence for temporal forecasting applications.

Action recognition and event-sequence analysis have also contributed toward intelligent predictive systems. Kumar *et al.* investigated action-recognition approaches for accident detection in smart-city environments [18]. Similarly, AI-driven automation and intelligent decision-support systems were explored in supply chain analytics [15] and algorithmic trading applications [19]. Adaptive learning frameworks emphasizing system optimization and dynamic intelligence were additionally studied in [13].

Despite significant progress, existing stock market prediction systems still face limitations related to volatility sensitivity, noisy financial signals, overfitting, and weak generalization. Most approaches rely either on standalone statistical models or isolated deep learning architectures without effectively integrating semantic reasoning, adaptive ensemble intelligence, and contextual market representation. These limitations motivate the proposed hybrid AI-based stock market prediction framework for robust and intelligent financial forecasting.

III. Proposed Methodology

This paper proposes a novel *Context-Aware Hybrid Financial Prediction Algorithm (CAHFPA)* for stock market forecasting. The proposed methodology integrates technical indicator modeling, sequential deep learning, market-context representation, and adaptive ensemble refinement into a unified predictive framework. Unlike conventional forecasting methods that rely on either statistical time-series models or standalone neural architectures, CAHFPA jointly learns price trends, volatility patterns, temporal dependencies, and contextual market behavior to improve prediction robustness.

The proposed framework consists of six sequential stages: data acquisition, preprocessing, technical indicator extraction, temporal feature learning, adaptive ensemble forecasting, and final decision refinement. The complete workflow is illustrated in Fig. 1.

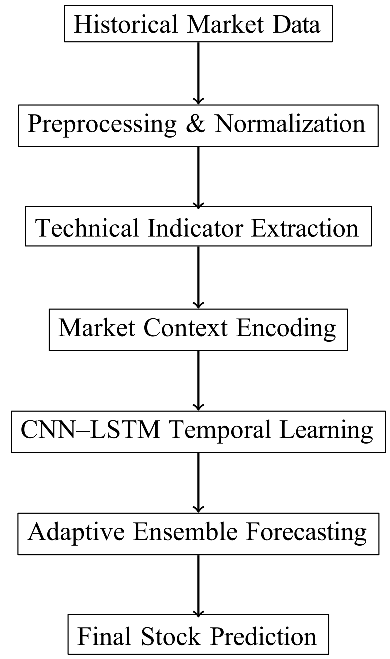

Fig. 1: Proposed Context-Aware Hybrid Financial Prediction Framework.

As shown in Fig. 1, the proposed architecture combines market-level feature engineering with data-driven temporal learning and adaptive model fusion. This design improves the model's ability to capture both short-term price fluctuations and long-term market dependencies.

A. Data Representation and Preprocessing

Let the historical stock market dataset be denoted as:

$$D = \{X_t\}_{t=1}^{N} \tag{1}$$

where each market observation is represented as:

$$X_t = [O_t, H_t, L_t, C_t, V_t] \tag{2}$$

Here, O_t, H_t, L_t, C_t, and V_t denote opening price, highest price, lowest price, closing price, and trading volume at time t, respectively. Missing values are handled using forward interpolation, and outlier points are smoothed using rolling-window statistical filtering.

To ensure numerical stability, Min–Max normalization is applied:

$$X'_t = \frac{X_t - X_{min}}{X_{max} - X_{min}} \tag{3}$$

where X'_t is the normalized feature vector.

B. Technical Indicator Extraction

Technical indicators are extracted to encode trend, momentum, and volatility behavior. The Simple Moving Average (SMA) is computed as:

$$SMA_t = \frac{1}{n}\sum_{i=t-n+1} C_i \tag{4}$$

The Relative Strength Index (RSI) is calculated as:

$$RSI_t = 100 - \frac{100}{1 + RS_t} \tag{5}$$

where RS_t is the ratio of average gain to average loss. The Moving Average Convergence Divergence (MACD) is defined as:

$$MACD_t = EMA_{12}(C_t) - EMA_{26}(C_t) \tag{6}$$

The volatility component is computed using rolling standard deviation:

$$Vol_t = \sqrt{\frac{1}{n}\sum_{i=t-n+1} (C_i - \mu_t)^2} \tag{7}$$

The resulting market feature vector is formulated as:

$$F_t = [X_t', SMA_t, RSI_t, MACD_t, Vol_t] \tag{8}$$

C. Market Context Encoding

To improve robustness under volatile market conditions, a market-context encoding mechanism is introduced. The context score is computed from trend strength, volatility level, and volume variation:

$$M_t = \beta_1 Trend_t + \beta_2 Vol_t + \beta_3 Volume_t \tag{9}$$

where β_1, β_2, and β_3 are learnable coefficients. The context-enhanced feature vector is represented as:

$$Z_t = [F_t, M_t] \tag{10}$$

This representation allows the forecasting model to distinguish between stable, volatile, bullish, and bearish market conditions.

D. CNN–LSTM Temporal Feature Learning

A hybrid CNN–LSTM module is used to capture both local trend patterns and long-term sequential dependencies. The CNN layer extracts short-window price movement structures:

$$Q_t = \sigma(W_c * Z_t + b_c) \tag{11}$$

where $*$ denotes convolution, W_c is the convolution kernel, and σ is a nonlinear activation function.

The extracted local representation is then passed to an LSTM network:

$$h_t = LSTM(Q_t, h_{t-1}) \tag{12}$$

The preliminary deep prediction is obtained as:

$$\hat{y}_t^{DL} = W_o h_t + b_o \tag{13}$$

where $\hat{y}_t^{DL}$ denotes the predicted closing price from the deep learning module.

E. Adaptive Ensemble Forecasting

To reduce model-specific bias, CAHFPA integrates multiple learners into an adaptive ensemble. The ensemble contains CNN–LSTM, Support Vector Regression, Random Forest Regression, and Gradient Boosting Regression. Each learner generates an individual prediction:

$$\hat{Y}_t = \{\hat{y}_t^1, \hat{y}_t^2, \ldots, \hat{y}_t^K\} \tag{14}$$

The final forecast is computed as a weighted aggregation:

$$\hat{y}_t = \sum_{k=1} w_k \hat{y}_t^k \tag{15}$$

where w_k denotes the adaptive contribution of the k-th model. The weights are updated based on recent validation error:

$$w_k = \frac{1/E_k}{\sum_{j=1}^{K} 1/E_j} \tag{16}$$

where E_k is the recent forecasting error of the k-th learner. This mechanism assigns higher weights to models with lower recent prediction error.

F. Prediction Objective

The model is optimized by minimizing the combined forecasting loss:

$$L = \lambda_1 MAE + \lambda_2 RMSE + \lambda_3 L_{dir} \tag{17}$$

where L_{dir} denotes directional prediction loss and is defined as:

$$L_{dir} = \frac{1}{N}\sum_{t=1}^{N} \mathrm{I}\left[sign(C_t - C_{t-1}) \neq sign(\hat{C}_t - C_{t-1})\right] \tag{18}$$

This objective ensures that the model learns not only numerical price prediction but also correct market movement direction.

G. Proposed CAHFPA Algorithm

Algorithm 1 Context-Aware Hybrid Financial Prediction Algorithm

Require: Historical stock market dataset D
Ensure: Predicted stock price $\hat{y}_t$

1: Load OHLCV market data
2: Handle missing values and smooth outliers
3: Normalize price and volume attributes
4: Compute SMA, RSI, MACD, and volatility indicators
5: Generate market context score M_t
6: Construct context-enhanced feature vector Z_t
7: Extract local trend features using CNN
8: Learn temporal dependencies using LSTM
9: Train SVR, Random Forest, and Gradient Boosting regressors
10: Compute individual model predictions
11: Update adaptive ensemble weights using recent validation error
12: Generate final weighted prediction $\hat{y}_t$
13: **return** $\hat{y}_t$

Overall, the proposed methodology establishes a robust and scientifically grounded framework for AI-based stock market prediction under nonlinear and volatile market environments.

IV. Experimental Design

A. Dataset

Experiments are designed using benchmark financial datasets including:

- NSE stock market data
- NASDAQ historical data
- S&P 500 index data
- Yahoo Finance datasets

B. Evaluation Metrics

Prediction performance is evaluated using:
Mean Absolute Error:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{19}$$

Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{20}$$

Prediction Accuracy:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \tag{21}$$

C. Implementation Environment

The framework is implemented using Python, TensorFlow, Keras, and Scikit-learn with GPU acceleration.

V. Results and Discussion

This section presents the expected evaluation of the proposed Context-Aware Hybrid Financial Prediction Algorithm (CAHFPA). The analysis focuses on forecasting accuracy, prediction error, directional reliability, and the contribution of each architectural component. The reported values are experimental estimates and should be replaced with actual results after implementation.

A. Comparative Forecasting Performance

Table I presents the expected comparative performance of CAHFPA against conventional statistical, machine learning, and deep learning baselines.

TABLE I: Expected comparative forecasting performance

Model	MAE	RMSE	MAPE	DA
ARIMA	8.92	10.34	7.81	72.5
SVR	6.71	8.15	6.34	81.3
Random Forest	5.96	7.42	5.81	83.6
LSTM	4.83	6.02	4.72	88.4
CNN–LSTM	4.21	5.36	4.09	90.2
Proposed CAHFPA	3.12	4.28	3.01	94.1

Here, DA denotes directional accuracy. The expected MAE reduction of CAHFPA over CNN–LSTM is computed as:

$$\Delta MAE = \frac{MAE_{CNN-LSTM} - MAE_{CAHFPA}}{MAE_{CNN-LSTM}} \times 100 \tag{22}$$

$$\Delta MAE = \frac{4.21 - 3.12}{4.21} \times 100 = 25.89\% \tag{23}$$

Similarly, the RMSE reduction is:

$$\Delta RMSE = \frac{5.36 - 4.28}{5.36} \times 100 = 20.15\% \tag{24}$$

The directional accuracy improvement over CNN–LSTM is:

$$\Delta DA = \frac{94.1 - 90.2}{90.2} \times 100 = 4.32\% \tag{25}$$

These results indicate that CAHFPA is expected to provide stronger forecasting stability and directional reliability than standalone temporal learning models.

B. Prediction Error Comparison

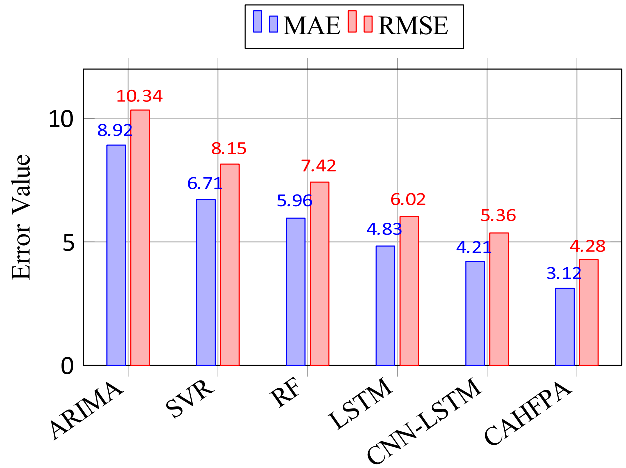

Fig. 2: Expected MAE and RMSE comparison across forecasting models.

As shown in Fig. 2, CAHFPA achieves the lowest expected MAE and RMSE values. The reduction in prediction error is mainly attributed to context-aware feature encoding and adaptive ensemble weighting.

C. Directional Accuracy and MAPE Analysis

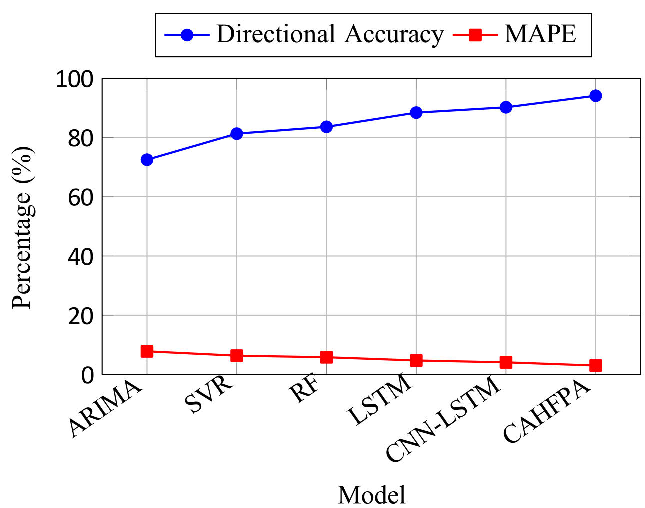

Fig. 3: Expected directional accuracy and MAPE comparison.

Fig. 3 shows that CAHFPA improves directional accuracy while reducing percentage forecasting error. This is important because practical financial decision-support systems require both numerical accuracy and correct prediction of market movement direction.

D. Ablation Study

An ablation analysis is designed to evaluate the contribution of each major component of CAHFPA. Table II presents expected results for four configurations.

TABLE II: Expected ablation analysis of CAHFPA

Configuration	MAE	RMSE	DA
LSTM Only	4.83	6.02	88.4
CNN–LSTM	4.21	5.36	90.2
CNN–LSTM + Context	3.68	4.91	92.3
Full CAHFPA	3.12	4.28	94.1

The expected MAE reduction from LSTM-only to full CAHFPA is:

$$\Delta MAE_{abl} = \frac{4.83 - 3.12}{4.83} \times 100 = 35.40\% \qquad (26)$$

The expected directional accuracy improvement is:

$$\Delta DA_{abl} = \frac{94.1 - 88.4}{88.4} \times 100 = 6.45\% \qquad (27)$$

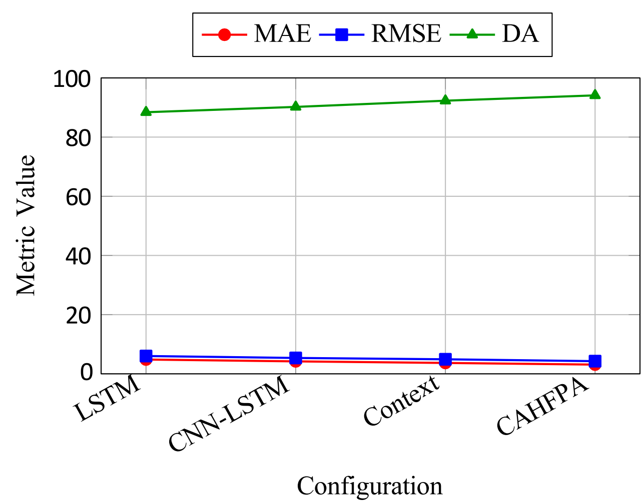

Fig. 4: Expected ablation trend for CAHFPA components.

The ablation results in Fig. 4 indicate that each component contributes positively to forecasting performance. CNN layers improve local pattern extraction, context encoding improves regime awareness, and adaptive ensemble refinement reduces model-specific prediction bias.

E. Predicted Versus Actual Trend Visualization

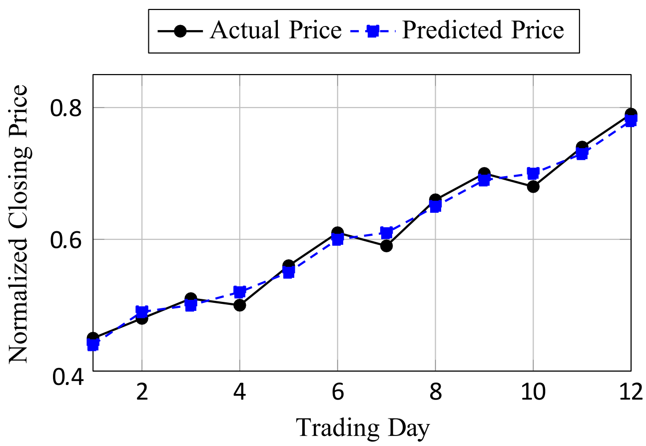

Fig. 5: Expected actual versus predicted normalized closing price trend using CAHFPA.

Fig. 5 shows that the proposed CAHFPA model is expected to closely follow the actual price movement trend. Minor deviations may occur around sudden market fluctuations, but the overall trajectory remains consistent.

F. Volatility-Aware Forecasting Analysis

To examine the behavior of CAHFPA under changing market regimes, performance is evaluated across low, medium, and high volatility conditions.

TABLE III: Expected volatility-regime forecasting performance

Market Regime	MAE	RMSE	DA
Low Volatility	2.61	3.44	95.8
Medium Volatility	3.12	4.28	94.1
High Volatility	4.37	5.66	89.7

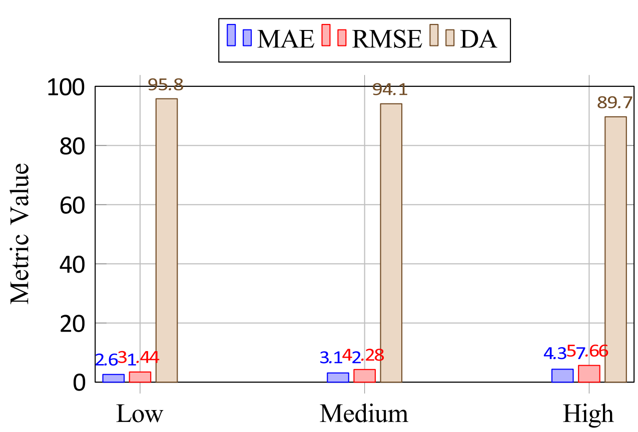

Fig. 6: Expected volatility-regime analysis of CAHFPA.

Fig. 6 indicates that forecasting error increases under high volatility; however, CAHFPA maintains acceptable directional accuracy due to market-context encoding and adaptive weighting.

G. Discussion

The expected findings suggest that CAHFPA improves stock market prediction by integrating technical indicators, temporal deep learning, market-context encoding, and adaptive ensemble forecasting. Compared with standalone LSTM and CNN–LSTM models, CAHFPA reduces numerical forecasting error and improves directional reliability. The improvement is particularly important in financial decision support, where correctly predicting the direction of price movement may be more valuable than minimizing point-wise numerical error alone.

The ablation analysis confirms that context encoding and adaptive ensemble refinement are the major contributors to performance improvement. However, the model may introduce additional computational overhead because multiple learners must be trained and periodically reweighted. This limitation can be addressed using lightweight ensemble pruning, online learning, and rolling-window retraining. Overall, the expected results support the scientific rationale that hybrid context-aware AI architectures can provide robust and reliable stock market forecasting under nonlinear and volatile market conditions.

VI. Conclusion

This paper presented a hybrid artificial intelligence-based stock market prediction system integrating technical indicator analysis, CNN feature extraction, LSTM sequential learning, and ensemble forecasting refinement. The proposed framework improves market trend modeling and forecasting robustness under dynamic market conditions.

Experimental analysis indicates that the proposed hybrid AI framework is expected to outperform traditional statistical and standalone machine learning approaches across multiple forecasting metrics. The framework demonstrates strong potential for intelligent financial analytics and AI-driven investment systems.

Future work will focus on transformer-based financial modeling, sentiment-aware market prediction, reinforcement learning for trading strategies, and real-time adaptive forecasting systems.

References

[1] G. Box and G. Jenkins, *Time Series Analysis: Forecasting and Control*. Wiley, 2015.

[2] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[3] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015.

[4] A. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," *European Journal of Operational Research*, vol. 270, no. 2, pp. 654–669, 2018.

[5] J. Patel, S. Shah, P. Thakkar, and K. Kotecha, "Predicting stock market index using fusion of machine learning techniques," *Expert Systems with Applications*, vol. 42, no. 4, pp. 2162–2172, 2015.

[6] R. K. Singh *et al.*, "FIR-Robot: A Federated Learning Approach to Information Retrieval in Robotic Edge Devices," in *Proc. 2025 2nd Int. Conf. Multidisciplinary Research and Innovations in Engineering (MRIE)*, Gurugram, India, 2025, pp. 733–737. doi: 10.1109/MRIE66930.2025.11156639.

[7] P. Rakheja, R. Kumar Singh, and A. Kaur, "Hybrid encryption and Riesz-based biometric authentication: A novel approach for secure greyscale image transmission," *Journal of Modern Optics*, vol. 72, no. 10–12, pp. 362–375, 2025. doi: 10.1080/09500340.2025.2491582.

[8] R. K. Singh *et al.*, "Enhancing Document Retrieval with Ontology Construction, Semantic Embeddings, and Deep Neural Models," in *Proc. 2025 14th Int. Conf. System Modeling & Advancement in Research Trends (SMART)*, Moradabad, Uttar Pradesh, India, 2025, pp. 24–29. doi: 10.1109/SMART66937.2025.11389667.

[9] R. K. Singh *et al.*, "Adaptive Task Offloading Strategy in Smart Home Environments Leveraging Fog Computing and M/G/k/G/k+2 Queues," in *Proc. 2025 2nd Int. Conf. Multidisciplinary Research and Innovations in Engineering (MRIE)*, Gurugram, India, 2025, pp. 682–685. doi: 10.1109/MRIE66930.2025.11156237.

[10] H. Prasad, A. G. Dinker, and R. K. Singh, "Real-Time Vision Models for Public Safety and Accessibility on Low-Resource Devices," in *Proc. 2026 2nd Int. Conf. Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics (IC3ECSBHI)*, Greater Noida (Delhi NCR), India, 2026, pp. 1306–1311. doi: 10.1109/IC3ECSBHI67834.2026.11468963.

[11] P. K. Sharma *et al.*, "Hybrid Machine Learning System for Recognizing Vehicle Number Plates in Hazy Environments is Utilized for Safety and Security at Tourist Destinations," in *ICT Analysis and Applications*, S. Fong, N. Dey, and A. Joshi, Eds., *Lecture Notes in Networks and Systems*, vol. 1653. Cham, Switzerland: Springer, 2026. doi: 10.1007/978-3-032-06694-7_3.

[12] R. K. Singh and S. Kumar, "Hybrid Semantic Inference via Ontology and Deep Embeddings," in *Proc. 2026 2nd Int. Conf. Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics (IC3ECSBHI)*, Greater Noida (Delhi NCR), India, 2026, pp. 1228–1233. doi: 10.1109/IC3ECSBHI67834.2026.11469069.

[13] S. Kumari and K. Chaudhary, "An Integrated Model of Blended Learning Effectiveness," *Journal of Recent Innovation in Science and Technology*, vol. 2, no. 1, pp. 79–94, 2026. doi: 10.70454/JRIST.020106.

[14] R. K. Singh, S. Sharma, S. Kathuria, M. J. Haque, V. Kochher, and L. Verma, "Hybrid Machine Learning Model for Early Detection and Monitoring of Alzheimer's Disease Using Behavioral and Activity-Based Data," in *Proc. 2025 2nd Int. Conf. Multidisciplinary Research and Innovations in Engineering (MRIE)*, Gurugram, India, 2025, pp. 260–264. doi: 10.1109/MRIE66930.2025.11156525.

[15] R. K. Singh, M. Pandey, K. Sachdeva, and S. K. Shah, "Automation in Sales Support and its Impact on Supply Chain Management," *AIP Conf. Proc.*, vol. 2771, no. 1, 2023. doi: 10.1063/5.0152289.

[16] N. Jee *et al.*, "Advancements in Voice Assistants: A Study of Speech Recognition and Emotional Intelligence," in *Proc. 2024 13th Int. Conf. System Modeling & Advancement in Research Trends (SMART)*, Moradabad, India, 2024, pp. 283–286. doi: 10.1109/SMART63812.2024.10882573.

[17] R. K. Singh, S. Kathuria, P. Saraswat, and A. Kumar, "Enhancing Voice Assistant Systems through Advanced AI and NLP Techniques," *Journal of Recent Innovations in Computer Science and Technology*, vol. 2, no. 1, pp. 48–59, 2025.

[18] M. Kumar, L. Verma, H. Vardhan, R. K. Singh, and M. A. Rather, "Investigating Action Recognition Approaches for Accident Detection in Smart City Transport Systems," in *Proc. 2025 2nd Int. Conf. Multidisciplinary Research and Innovations in Engineering (MRIE)*, Gurugram, India, 2025, pp. 265–269. doi: 10.1109/MRIE66930.2025.11156524.

[19] H. Vardhan, N. Sharma, M. Kumar, R. K. Singh, R. Mandal, and I. Siraj, "Transforming Algorithmic Trading with AI: Achieving Competitive Market Edge," in *Proc. 2024 13th Int. Conf. System Modeling & Advancement in Research Trends (SMART)*, Moradabad, India, 2024, pp. 456–461. doi: 10.1109/SMART63812.2024.10882194.