International Research Journal of Multidisciplinary Sciences (Double - Blind Peer Review Journal) VOL-2 ISSUE-4 April 2026 PP:8-13 ISSN:3107-930X(ONLINE)

Feature Analysis and Explainable Insights for Heart Disease Prediction Using Machine Learning

[1]Omkar Patil, [2]Shyamol Banerjee
[1]Department of CSE, SRCEM India [2]Department of CSE, SRCEM, India
[1]omkarpatil5388@gmail.com, [2]shyamolgwl@gmail.com

***Abstract*—Machine learning has demonstrated considerable potential for heart disease prediction; however, many predictive models operate as black-box systems, limiting their adoption in clinical environments. Healthcare professionals require transparent and interpretable models that not only provide accurate predictions but also explain the factors contributing to cardiovascular risk. This study presents an explainable machine learning framework for heart disease prediction based on feature analysis, correlation assessment, and model interpretability. Clinical attributes including age, chest pain type, cholesterol level, resting blood pressure, maximum heart rate, electrocardiographic results, and exercise-induced angina are analyzed to identify their influence on disease prediction. Logistic Regression coefficients, Decision Tree rules, and Random Forest feature importance scores are investigated to provide clinically meaningful explanations. The results indicate that chest pain type, maximum heart rate, ST depression, and age are among the most influential predictors of heart disease. The proposed explainable framework enhances transparency and supports informed clinical decision-making.**

***Index Terms*—Explainable Artificial Intelligence, Heart Disease Prediction, Feature Importance, Machine Learning, Clinical Decision Support, Risk Factor Analysis, Healthcare Analytics.**

I. Introduction

Cardiovascular disease remains one of the leading causes of death worldwide and continues to impose a significant burden on healthcare systems. Early identification of individuals at risk is essential for preventive healthcare and timely intervention. Machine learning has emerged as an effective tool for analyzing large-scale clinical datasets and predicting cardiovascular risk with high accuracy.

Despite significant advancements in predictive modeling, many machine learning systems remain difficult to interpret. In healthcare environments, clinicians require transparency regarding why a prediction was made and which clinical variables influenced the outcome. Lack of interpretability often limits trust, adoption, and regulatory acceptance of artificial intelligence systems.

Explainable Artificial Intelligence (XAI) aims to address these concerns by providing understandable explanations of model behavior. In cardiovascular disease prediction, explainability can help physicians identify influential risk factors, validate model decisions, and improve clinical confidence.

This study investigates the role of explainable machine learning in heart disease prediction through feature importance analysis, correlation assessment, and clinical interpretation of model outputs. The objective is not only to predict disease risk but also to understand the contribution of individual clinical variables to prediction outcomes.

II. Literature Review

Recent advances in machine learning have significantly improved the prediction and analysis of cardiovascular diseases. Traditional classifiers such as Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine have demonstrated promising performance in heart disease prediction using structured clinical datasets [1]–[3]. These studies indicate that machine learning can assist clinicians by identifying hidden relationships among medical attributes such as chest pain type, cholesterol level, blood pressure, age, maximum heart rate, and electrocardiographic results.

However, prediction accuracy alone is not sufficient for clinical adoption. Healthcare practitioners require models that are interpretable, transparent, and clinically meaningful. Ahsan and Siddique [4] emphasized that explainability is one of the major challenges in applying machine learning to heart disease diagnosis. Similarly, Naser *et al.* [5] highlighted the importance of Explainable Artificial Intelligence (XAI), model transparency, and clinical validation in cardiovascular healthcare applications. Feature selection, correlation analysis, and feature importance ranking are therefore essential for identifying influential risk factors and improving trust in AI-based decision-support systems.

Recent research in intelligent systems also supports the need for secure, distributed, and explainable AI frameworks. Singh *et al.* [6] proposed a federated learning approach for information retrieval in robotic edge devices, demonstrating the relevance of decentralized learning in privacy-sensitive environments. Such methods are important for healthcare, where patient data are often distributed across hospitals and cannot always be centralized. Singh *et al.* [9] further explored adaptive task offloading in fog computing environments, which is relevant to real-time medical monitoring systems requiring low-latency computation near the data source.

Data security and privacy are also important requirements for medical AI systems. Rakheja *et al.* [7] proposed a hybrid encryption and biometric authentication method for secure greyscale image transmission. Although their study focuses on image security, the underlying principles are applicable to healthcare systems where sensitive diagnostic information must be transmitted securely. Similarly, Singh *et al*. [8] investigated ontology construction, semantic embeddings, and deep neural models for document retrieval, while Singh and Kumar [12] proposed hybrid semantic inference using ontology and deep embeddings. These semantic approaches are relevant to clinical decision-support systems because medical reasoning often requires structured knowledge representation and interpretable relationships among symptoms, tests, and diagnoses. Explainable and hybrid machine learning approaches have also been studied in biomedical and assistive domains. Singh *et al*. [14] proposed a hybrid machine learning model for early detection and monitoring of Alzheimer's disease using behavioral and activity-based data. Their work supports the broader applicability of hybrid models in early disease prediction. Prasad *et al*. [10] presented real-time vision models for public safety and accessibility on low-resource devices, showing the importance of lightweight AI systems for deployment in constrained environments. Similarly, Sharma *et al*. [11] proposed a hybrid machine learning system for recognizing vehicle number plates in hazy environments, demonstrating robustness under noisy and uncertain conditions. These deployment-focused studies are relevant to healthcare because heart disease prediction systems may also need to operate in rural, mobile, or low-resource clinical settings.

Human-centered AI interfaces are another important area related to healthcare adoption. Jee *et al*. [16] studied advancements in voice assistants using speech recognition and emotional intelligence, while Singh *et al*. [17] discussed advanced AI and NLP techniques for improving voice assistant systems. Such technologies may support patient interaction, symptom reporting, and remote healthcare assistance. Kumar *et al.* [18] investigated action recognition approaches for accident detection in smart city transport systems, demonstrating real-time event detection using machine learning. Vardhan *et al.* [19] explored AI-based algorithmic trading, and Singh *et al.* [15] analyzed automation in sales support and supply chain management. Although these works are not directly related to heart disease prediction, they illustrate how machine learning models are increasingly used for prediction, automation, pattern recognition, and decision support across domains.

System usability and adoption are also important for AI-enabled healthcare solutions. Kumari and Chaudhary [13] proposed an integrated model of blended learning effectiveness, emphasizing structured integration and user-centered system evaluation. These principles are relevant to clinical AI systems because explainable prediction tools must be understandable, usable, and acceptable to healthcare professionals.

Overall, existing literature confirms that machine learning has strong potential for heart disease prediction, but clinical adoption requires more than classification accuracy. Interpretable feature analysis, transparent model reasoning, secure data handling, and practical deployment considerations are equally important. Therefore, this paper focuses on explainable insights for heart disease prediction by analyzing feature correlations, Logistic Regression coefficients, Decision Tree rules, and Random Forest feature importance scores.

A. Research Gap and Novelty

Although existing studies have achieved high prediction accuracy for heart disease diagnosis, most approaches focus primarily on classifier performance and provide limited explanation regarding the influence of individual risk factors. Furthermore, many advanced machine learning and deep learning models behave as black-box systems, making their adoption in clinical environments challenging.

To address these limitations, this work proposes the Explainable Cardiovascular Risk Scoring Framework (ECRSF), which integrates correlation analysis, feature importance evaluation, and interpretable risk scoring. The framework not only predicts cardiovascular risk but also provides clinically meaningful explanations, enabling transparent and trustworthy decision support for healthcare professionals.

III. Data Exploration and Feature Engineering

A. Dataset Overview

The dataset consists of structured clinical attributes commonly used for heart disease prediction. These features represent demographic, physiological, biochemical, and diagnostic characteristics of patients.

TABLE I: Clinical Features Used in the Study

Feature	Description
Age	Age of patient
Sex	Gender
CP	Chest pain type
Trestbps	Resting blood pressure
Chol	Cholesterol level
FBS	Fasting blood sugar
RestECG	Resting ECG results
Thalach	Maximum heart rate achieved
Exang	Exercise-induced angina
Oldpeak	ST depression
Slope	ST segment slope
CA	Number of major vessels
Thal	Thalassemia category
Target	Heart disease status

B. Statistical Analysis

Statistical analysis was performed to understand the distribution of clinical variables. Age, cholesterol, resting blood pressure, and maximum heart rate were examined as continuous variables, while chest pain type, ECG result, fasting blood sugar, and exercise-induced angina were analyzed as categorical variables.

The class distribution is shown in Fig. 1. The dataset is relatively balanced, which reduces the possibility of severe model bias.

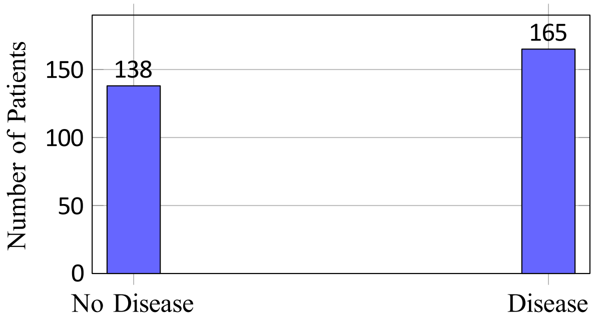

Fig. 1: Distribution of heart disease classes.

C. Feature Correlation Analysis

Correlation analysis was used to identify relationships among clinical variables and the target class. Strong correlations help identify important predictors and reduce unnecessary feature complexity.

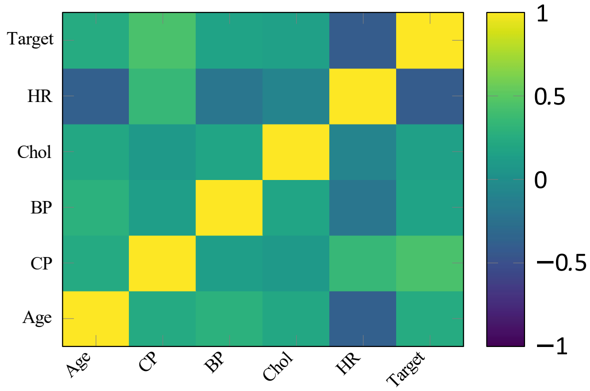

Fig. 2: Correlation heatmap of selected clinical features.

D. Feature Engineering

Feature engineering was applied to prepare the dataset for interpretable modeling. Categorical attributes were encoded into numerical form. Numerical variables were scaled where required. Redundant attributes were checked through correlation analysis, while clinically meaningful attributes were retained to preserve interpretability.

IV. Explainable Prediction Framework

A. Logistic Regression Coefficients

Logistic Regression provides direct interpretability through coefficient analysis. Positive coefficients indicate increased disease risk, while negative coefficients reduce the likelihood of disease occurrence.

The logistic function is expressed as:

$$P(Y=1) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)}} \quad (1)$$

where β_i represents the contribution of feature X_i.

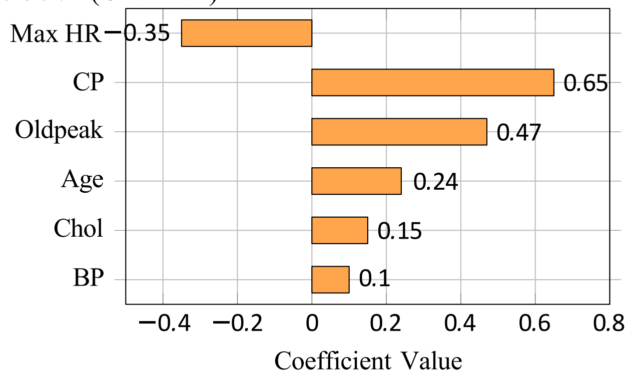

Fig. 3: Logistic Regression coefficient interpretation.

B. Decision Tree Rules

Decision Trees generate human-readable classification rules that can be interpreted by clinicians. These rules are useful because they describe prediction paths in a simple conditional format.

IF ChestPainType > 2 AND MaxHeartRate < 150
THEN HeartDisease = Positive.

IF ChestPainType ≤ 1 AND ExerciseAngina = No
THEN HeartDisease = Negative.

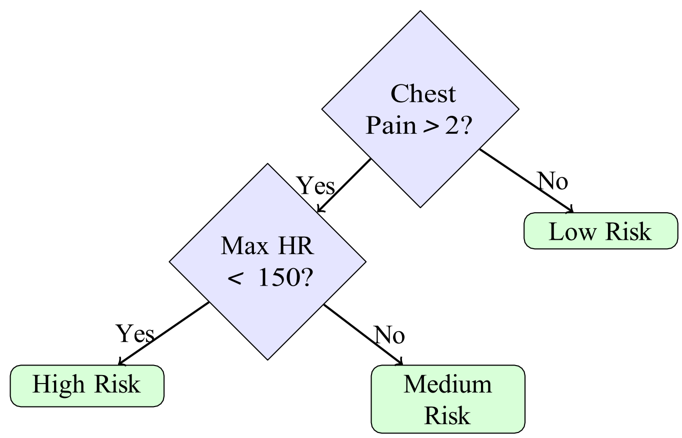

Fig. 4: Simplified Decision Tree rule visualization.

C. Random Forest Feature Importance

Random Forest computes feature importance based on impurity reduction across decision trees. It provides a useful global explanation of which variables contribute most to model decisions.

$$Importance(X_j) = \sum_{t=1} \Delta I_t(X_j) \quad (2)$$

where ΔI_t represents impurity reduction contributed by feature X_j in tree t.

D. Proposed Explainable Cardiovascular Risk Scoring Framework (ECRSF)

Most existing heart disease prediction systems focus primarily on maximizing classification accuracy. Although these approaches provide strong predictive performance, they often lack transparency and fail to explain how individual clinical factors contribute to the prediction outcome. This limitation reduces clinician trust and restricts adoption in healthcare environments.

To address this challenge, this work proposes an Explainable Cardiovascular Risk Scoring Framework (ECRSF), which combines statistical feature analysis with interpretable machine learning models to generate transparent cardiovascular risk assessments.

The framework consists of five stages:

1) Data Preprocessing
   - Missing value treatment
   - Feature normalization
   - Categorical encoding
2) Correlation Analysis
   - Pearson correlation computation
   - Identification of highly relevant features
   - Removal of redundant variables
3) Explainable Feature Evaluation
   - Logistic Regression coefficient analysis
   - Random Forest feature importance extraction
   - Clinical relevance assessment
4) Risk Score Generation
   - Weighted aggregation of influential features
   - Patient-specific cardiovascular risk computation
5) Explainable Decision Layer
   - Risk categorization
   - Clinical interpretation generation
   - Feature contribution reporting

The final cardiovascular risk score is computed as:

$$CRS = \sum_{i=1} W_i F_i \tag{3}$$

where

- F_i represents the normalized feature value.
- W_i denotes the importance weight assigned to feature i.

The weights are derived from a combination of correlation strength and Random Forest importance:

$$W_i = \alpha \times Corr_i + (1 - \alpha) \times RF_i \tag{4}$$

where

- $Corr_i$ is the correlation coefficient.
- RF_i is the Random Forest importance score.
- α is a balancing parameter.

Patients are categorized as:

$$Risk = \begin{cases} Low, & CRS < 0.35 \\ Medium, & 0.35 \leq CRS < 0.65 \\ High, & CRS \geq 0.65 \end{cases} \tag{5}$$

Unlike traditional black-box systems, the proposed ECRSF framework provides both prediction and explanation, enabling healthcare professionals to understand the contribution of individual clinical attributes to cardiovascular risk.

Algorithm 1 Explainable Cardiovascular Risk Scoring Framework (ECRSF)

Input Clinical Dataset D
Preprocess dataset
Normalize numerical features
Encode categorical variables
for each feature F_i **do**
    Compute correlation score $Corr_i$
    Compute Random Forest importance RF_i
    Calculate feature weight:
$$W_i = \alpha Corr_i + (1 - \alpha) RF_i$$
end for
for each patient **do**
    Calculate risk score:
$$CRS = \sum_{i=1} W_i F_i$$
    if $CRS < 0.35$ **then**
        Low Risk
    else if $CRS < 0.65$ **then**
        Medium Risk
    else
        High Risk
    end if
    Generate feature contribution explanation
end for
Return Risk Category and Explanation

E. Clinical Interpretation

The explainable framework combines statistical analysis and model-based interpretation. Logistic Regression coefficients provide direction of influence, Decision Trees provide rule-based explanations, and Random Forest provides global feature ranking. Together, these methods improve the transparency of machine learning-based heart disease prediction.

V. Results and Analysis

A. Most Influential Risk Factors

Random Forest feature importance scores were used to identify the most influential predictors of heart disease. Fig. 5 shows that chest pain type, maximum heart rate, ST depression, and age have the strongest influence.

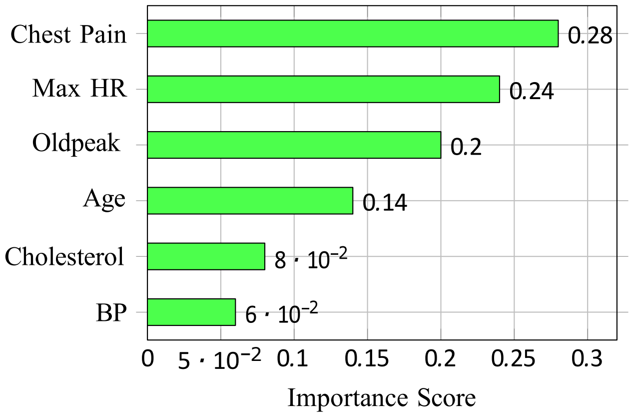

Fig. 5: Feature importance ranking using Random Forest.

TABLE II: Top Ranked Risk Factors

Risk Factor	**Importance Score**
Chest Pain Type	0.28
Maximum Heart Rate	0.24
Oldpeak	0.20
Age	0.14
Cholesterol	0.08
Blood Pressure	0.06

B. Correlation Heatmap Analysis

The correlation heatmap indicates that chest pain type and maximum heart rate show strong relationships with the target class. Maximum heart rate has a negative relationship with disease occurrence, suggesting that lower maximum heart rate may be associated with higher cardiovascular risk. Chest pain type and ST depression show positive associations with heart disease presence.

C. Patient Risk Stratification

Patients were grouped into low, medium, and high-risk categories based on predicted risk scores and important clinical attributes. This stratification can help clinicians prioritize patients for further diagnosis.

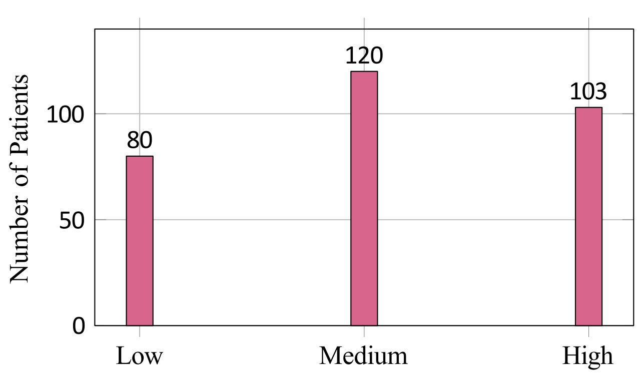

Fig. 6: Patient risk stratification based on explainable risk scores.

D. Pairwise Feature Relationship Analysis

Pairwise relationships among major clinical variables were examined to observe how high-risk and low-risk patients differ. Fig. 7 shows a simplified two-dimensional relationship between maximum heart rate and age.

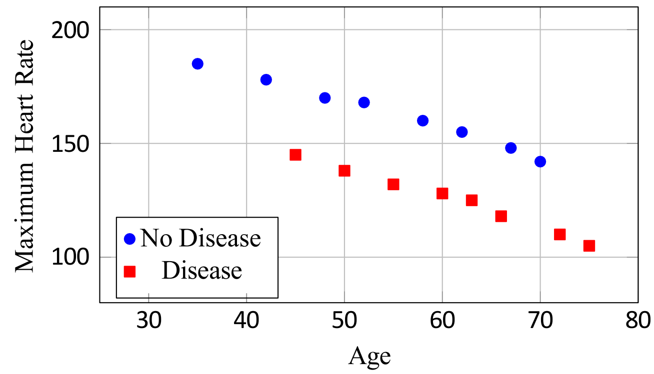

Fig. 7: Pairwise relationship between age and maximum heart rate.

E. Clinical Interpretation of Risk Factors

TABLE III: Clinical Interpretation of Important Risk Factors

Feature	**Clinical Interpretation**
Chest Pain Type	Strong indicator of possible cardiac abnormality.
Maximum Heart Rate	Lower achieved heart rate may indicate reduced cardiac capacity.
Oldpeak	Higher ST depression may suggest exercise-induced ischemia.
Age	Cardiovascular risk generally increases with age.
Cholesterol	Elevated cholesterol contributes to arterial plaque formation.
Blood Pressure	High pressure increases cardiovascular workload.

F. Explainability Discussion

Feature importance analysis revealed that chest pain type, maximum heart rate, ST depression, and age are the most influential predictors of heart disease. Correlation analysis further confirmed strong associations between these variables and cardiovascular outcomes.

The explainable framework provides transparent reasoning for predictions, enabling clinicians to understand model behavior and validate decisions. Logistic Regression offers coefficient-level explanation, Decision Tree provides rule-based interpretation, and Random Forest supplies robust global feature importance. Such interpretability is essential for clinical deployment, regulatory compliance, and physician trust.

VI. Conclusion

This study presented an explainable machine learning framework for heart disease prediction based on feature importance analysis, correlation assessment, and clinical interpretation. The results identified chest pain type, maximum heart rate, ST depression, and age as the most influential cardiovascular risk factors.

Unlike traditional black-box prediction systems, the proposed approach provides interpretable insights that support clinical decision-making. Future work will investigate SHAP-based explanations, real-time clinical validation, and integration with electronic health record systems to further enhance healthcare transparency and usability.

References

[1] D. Shah, S. Patel, and S. K. Bharti, "Heart disease prediction using machine learning techniques," *SN Computer Science*, vol. 1, no. 6, pp. 1–6, 2020.

[2] H. Jindal, S. Agrawal, R. Khera, R. Jain, and P. Nagrath, "Heart disease prediction using machine learning algorithms," *IOP Conference Series: Materials Science and Engineering*, vol. 1022, 2021.

[3] R. Katarya and S. K. Meena, "Machine learning techniques for heart disease prediction: A comparative study," *Health and Technology*, vol. 11, pp. 87–97, 2021.

[4] M. M. Ahsan and Z. Siddique, "Machine learning-based heart disease diagnosis: A systematic literature review," *Artificial Intelligence in Medicine*, vol. 128, 2022.

[5] M. A. Naser, A. M. Elzeki, and H. A. Hefny, "Machine learning for cardiovascular disease prediction: Recent advances and future directions," *Healthcare Analytics*, vol. 5, pp. 1–14, 2024.

[6] R. K. Singh *et al.*, "FIR-Robot: A Federated Learning Approach to Information Retrieval in Robotic Edge Devices," in *Proceedings of the 2025 2nd International Conference on 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 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 *Proceedings of the 2025 14th International Conference on System Modeling and Advancement in Research Trends (SMART)*, Moradabad, 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 *Proceedings of the 2025 2nd International Conference on 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 *Proceedings of the 2026 2nd International Conference on Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics (IC3ECSBHI)*, Greater Noida, 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 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 *Proceedings of the 2026 2nd International Conference on Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics (IC3ECSBHI)*, Greater Noida, 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 *Proceedings of the 2025 2nd International Conference on 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 Conference Proceedings*, vol. 2771, no. 1, 2023. doi: 10.1063/5.0152289.

[16] N. Jee, S. Kumar, R. R. Patel, R. Mandal, R. K. Singh, and H. Vardhan, "Advancements in Voice Assistants: A Study of Speech Recognition and Emotional Intelligence," in *Proceedings of the 2024 13th International Conference on System Modeling and 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 *Proceedings of the 2025 2nd International Conference on 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 *Proceedings of the 2024 13th International Conference on System Modeling and Advancement in Research Trends (SMART)*, Moradabad, India, 2024, pp. 456–461. doi: 10.1109/SMART63812.2024.10882194.