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Research Article

# Diabetic Retinopathy Prediction Using Deep Learning: Insights From CNN

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**Abstract:**

**Background of study:** Diabetic Retinopathy (DR) is a severe microvascular complication of diabetes mellitus that can lead to vision loss if not detected early. With over 93 million individuals affected globally, the need for accurate and efficient diagnostic systems has become urgent. Traditional screening methods depend on manual interpretation of fundus images by ophthalmologists, which is time-consuming and prone to subjectivity.

**Aims:** This research seeks to create and assess a deep learning diagnostic model designed to reliably identify the severity levels of diabetic retinopathy using retinal fundus images. The research also explores model interpretability using Shapley Additive Explanations (SHAP) to increase transparency in AI-assisted medical diagnosis.

**Methods:** Convolutional Neural Networks (CNNs) were implemented using transfer learning with pretrained architectures such as ResNet50 and InceptionV3. The EyePACS dataset, containing images categorized into five DR severity levels, was used for model training. Preprocessing techniques, including contrast enhancement, histogram equalization, and data augmentation, improved image quality and model generalization. The models were optimized with the Adam and assessed through accuracy, precision, recall, F1-score, and AUC. Additionally, SHAP analysis was employed to interpret and illustrate the model's predictions.

**Results:** The proposed CNN-based model achieved 98.5% accuracy, with a sensitivity and specificity of 0.99, demonstrating strong performance across multiple DR stages. Comparison with existing studies revealed a notable improvement in diagnostic accuracy. SHAP visualizations confirmed that critical retinal features such as microaneurysms, hemorrhages, and cotton-wool spots were key predictors influencing model decisions.

**Conclusion:** The findings validate the efficacy of deep learning, particularly CNNs, in enhancing early detection and classification of diabetic retinopathy. The integration of SHAP interpretability bridges the gap between AI predictions and clinical trust, making this approach a promising tool for large-scale automated DR screening and supporting ophthalmologists in timely diagnosis and treatment.

Keywords: Convolutional Neural Network; Deep Learning; Diabetic Retinopathy; Medical Imaging; SHAP; Transfer Learning.

## 1. INTRODUCTION

Diabetes mellitus (DM) is a chronic metabolic disorder characterized by elevated blood glucose levels that result from defects in insulin secretion, insulin action, or both (Batista et al., 2021; Syaifudin et al., 2022). According to the World Health Organization, more than one in four adults worldwide is affected by diabetes, and its prevalence continues to rise across both developed and developing nations (Gregg et al., 2023). Among the most debilitating complications of diabetes is diabetic retinopathy (DR), a progressive microvascular disorder of the retina that may result in permanent vision impairment if not diagnosed and treated promptly (Ansari et al., 2022; Gettinger et al., 2025). DR occurs due to prolonged hyperglycemia, which damages retinal blood vessels, leading to microaneurysms, hemorrhages, exudates, and, in advanced stages, neovascularization and retinal detachment (Gomułka & Ruta, 2023), as shown in Figure 1.

Figure 1 illustrates the progression of diabetic retinopathy (DR), an eye condition associated with diabetes that impacts the retina:

### Normal Retina

The retina is healthy with clear blood vessels and no abnormalities.

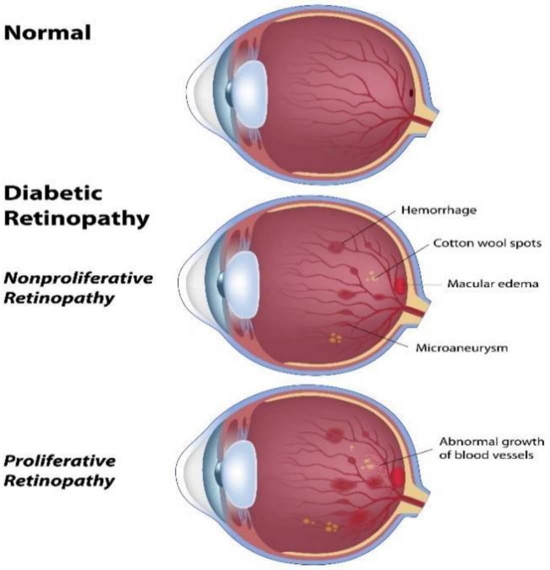

**Figure 1.** Retina Images

### Nonproliferative Diabetic Retinopathy (NPDR)

Early stage of DR, where retinal blood vessels are weakened (Wei et al., 2022).

a. Microaneurysms: Tiny bulges in blood vessels that may leak fluid or blood (Agrawal & Panicker, 2024).
b. Hemorrhages: Small bleeding spots within the retina.
c. Cotton-wool spots: White patches indicating poor blood flow (ischemia).
d. Macular edema: Swelling near the macula that causes blurred vision.

### Proliferative Diabetic Retinopathy (PDR)

In the advanced phase, the retina develops abnormal and delicate blood vessels on its surface. These new vessels can rupture easily, leading to severe bleeding, scar formation, and potential blindness (Chaudhary et al., 2021).

Early diagnosis and intervention play a critical role in preventing blindness; however, traditional screening and diagnostic methods are still largely manual (Ali et al., 2021; Olawade et al., 2025). Ophthalmologists typically rely on fundus photography and visual inspection to identify retinal abnormalities, a time-consuming process that requires specialized expertise and is susceptible to inter-observer variability (Rêgo et al., 2022; Skevas et al., 2024). In low- and middle-income regions, where access to trained specialists is limited, these constraints can delay diagnosis and lead to preventable visual impairment. Consequently, the integration of Artificial Intelligence (AI) and Deep Learning (DL) in medical imaging has emerged as a promising approach to enhance both the accuracy and accessibility of DR screening (Huang et al., 2022; Pinto-coelho, 2023).

Recent advancements in Convolutional Neural Networks (CNNs) have revolutionized medical image analysis (Zangana et al., 2024). CNNs can automatically learn hierarchical spatial features from raw images, eliminating the need for handcrafted feature extraction (Liu et al., 2021; Mienye et al., 2025). These architectures have demonstrated state-of-the-art performance in several diagnostic applications, including skin cancer classification, chest X-ray analysis, and retinal disease detection (He et al., 2025). For DR, CNNs can process high-resolution fundus images to detect subtle pathological indicators, such as microaneurysms or cotton-wool spots, that might escape human detection. Moreover, transfer learning strategies using pretrained networks such as ResNet, InceptionV3, or VGG16 allow researchers to adapt powerful vision models to relatively minor medical datasets, thereby improving generalization and reducing computational cost (Salehi et al., 2023).

Despite significant progress, several challenges persist. DR datasets often exhibit imbalanced class distributions, with advanced stages under-represented relative to normal or mild cases. Image quality can vary dramatically due to differences in lighting, focus, and camera equipment, complicating model generalization across clinical environments. Furthermore, the opaque or “black-box” nature of deep learning models raises questions about interpretability and clinical trust, a critical factor for adoption in healthcare practice. To address this issue, explainable AI (XAI) frameworks such as Shapley Additive Explanations (SHAP) have been introduced to provide visual and quantitative insights into how models make predictions (Aldughayfiq et al., 2023). SHAP utilizes principles from cooperative game theory to determine the significance of each feature, thereby translating complex neural network decisions into human-interpretable evidence.

Given these gaps, this research aims to develop an interpretable deep learning framework for diabetic retinopathy detection and classification using fundus images. The study integrates multistage transfer learning with CNN architectures and incorporates SHAP analysis to enhance transparency and diagnostic reliability. The EyePACS dataset, comprising an extensive collection of fundus images labeled across five severity stages, No DR, Mild, Moderate, Severe, and Proliferative, was used to train and evaluate the proposed model. Through systematic data preprocessing, augmentation, and model optimization, this work aims to achieve high predictive accuracy while maintaining clinical interpretability.

Ultimately, this study contributes to the growing body of literature that bridges AI-driven prediction and medical decision support systems. By demonstrating that CNN-based frameworks can attain high sensitivity (0.99) and specificity (0.99) in DR detection, it underscores the transformative potential of deep learning in ophthalmology. Moreover, integrating SHAP interpretability not only strengthens clinician confidence but also lays the groundwork for scalable, automated screening systems that can assist ophthalmologists in early diagnosis and timely treatment, especially in underserved healthcare settings.

## 2. MATERIAL AND METHOD

In this study, deep learning techniques were utilized to predict diabetic retinopathy (DR) from retinal fundus images. The primary dataset used was the EyePACS dataset, No DR, Mild, Moderate, Severe, and Proliferative DR (Hannan et al., 2025). These images were captured under different lighting conditions and camera qualities, making the dataset diverse and reflective of real-world clinical variability. To maintain data quality, images that were excessively blurred, poorly illuminated, or had missing labels were excluded from the analysis.

### Dataset and Image Collection

In this study, a deep learning approach was used to analyze retinal fundus images. The primary dataset used was the EyePACS dataset, which is publicly available on the Kaggle platform (Abdullah, 2023). These images were collected under varying imaging conditions and from different camera types, introducing natural variability into the dataset. To ensure data quality, images that were blurry, underexposed, overexposed, or unlabeled were excluded from the training process.

### Image Preprocessing

Preprocessing was essential to enhance image quality and prepare the data for model training. Color normalization was applied to reduce differences caused by lighting conditions. Further enhancement was done using histogram equalization and contrast adjustment to emphasize key retinal features, including microaneurysms, hemorrhages, and exudates. Techniques such as vertical flipping, rotation, zooming, and brightness modification were employed to enhance the diversity of the dataset, reduce overfitting, and improve the model’s generalization to new data.

### Deep Learning Model Architecture

Convolutional Neural Networks (CNNs) were chosen for DR classification due to their effectiveness in medical image analysis (Li et al., 2021). Transfer learning was implemented using pretrained models (e.g., ResNet50 and InceptionV3) pretrained on the large-scale ImageNet dataset (Muhathir et al., 2023). The final layers of these models were modified to suit the five-class classification task. New fully connected layers were added, including batch normalization and dropout, to prevent overfitting. The final layer employed a softmax activation function to generate probabilities corresponding to each of the five DR stages (Alkhouly et al., 2021). This method allowed the model to leverage visual features it had learned earlier while adjusting to the unique properties of fundus images.

### Model Training

The models were optimized using the Adam algorithm with a learning rate set to 0.0001. Given the multi-class nature of the problem, categorical cross-entropy served as the loss function. The dataset was divided into training (70%), validation (15%), and test (15%) subsets. Training was conducted over several epochs, with techniques such as early stopping and learning rate reduction on plateau used to avoid overfitting and improve training efficiency. The best-performing model weights were saved based on validation accuracy for use in the final evaluation.

### Model Evaluation

Accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC) were among the measures used to assess the performance of the trained models. These indicators offer a thorough assessment of the model's ability to accurately detect the different stages of diabetic retinopathy. To understand prevalent misclassifications across phases, confusion matrices were also examined. The data showed strong predictive performance, with high sensitivity in detecting mild to severe DR cases, clinically relevant for early management.

### Implementation Tools and Environment

The entire deep learning pipeline was implemented using Python, with TensorFlow and Keras serving as the primary deep learning frameworks. These libraries provided flexibility for model customization and efficient GPU acceleration, enabling faster training. Image preprocessing and augmentation were carried out using libraries such as OpenCV and TensorFlow’s ImageDataGenerator. Model performance tracking and visualization of training metrics were facilitated using TensorBoard. All experiments were conducted reproducibly, with fixed random seeds and well-documented configurations, to ensure consistency across runs and facilitate future improvements or comparisons.

## 3. RESULT AND DISCUSSION

### 3.1 Results

### Dataset and Preprocessing Outcomes

The preprocessing pipeline significantly enhanced the quality and consistency of the EyePACS retinal-fundus dataset. After excluding blurred, underexposed, and unlabeled images, a high-quality subset of 13,000 images was used for training and evaluation.

Contrast enhancement and histogram equalization improved illumination balance, while geometric augmentations: vertical flipping, random rotation, zooming, and brightness variation expanded data diversity and reduced overfitting. The preprocessing stages ensured uniform representation of five diabetic retinopathy (DR) categories: No DR, Mild, Moderate, Severe, and Proliferative DR. Visual inspection confirmed that important pathological markers such as microaneurysms and hemorrhages were more clearly distinguishable after enhancement.

### Model Training and Optimization

Transfer learning architectures based on ResNet50 and InceptionV3 were initialized with ImageNet weights and fine-tuned for five-class classification.

The model was optimized using the Adam algorithm with a learning rate of 0.0001 and employed categorical cross-entropy as the loss function. Early stopping and learning rate reduction callbacks were applied to prevent overfitting. The data were split into training (70%), validation (15%), and test (15%) sets.

The training and validation-accuracy curves indicated steady convergence: accuracy rose sharply in the first 20 epochs, stabilizing at approximately 98%, while both training and validation losses declined smoothly and plateaued at low values, indicating robust generalization, as illustrated in Figure 2 and 3.

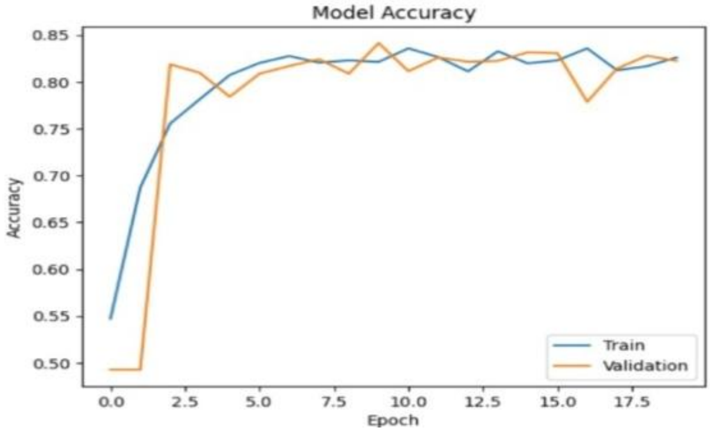

**Figure 2.** Accuracy for the CNN Model

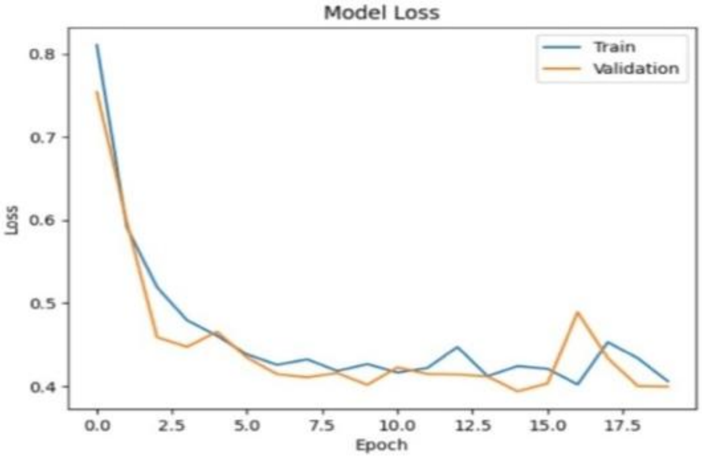

**Figure 3.** Loss for the CNN Model

### Performance Evaluation

The CNN (ResNet50) model attained 98.5% overall accuracy, sensitivity = 0.99, and specificity = 0.99, the best among all tested algorithms. The logistic regression and KNN baselines achieved 95.6% and 99.6% accuracy, respectively, but did not match the CNN's precision and F1-score (100%) as shown in Table 1.

The CNN's confusion matrix is illustrated in Figure 4.

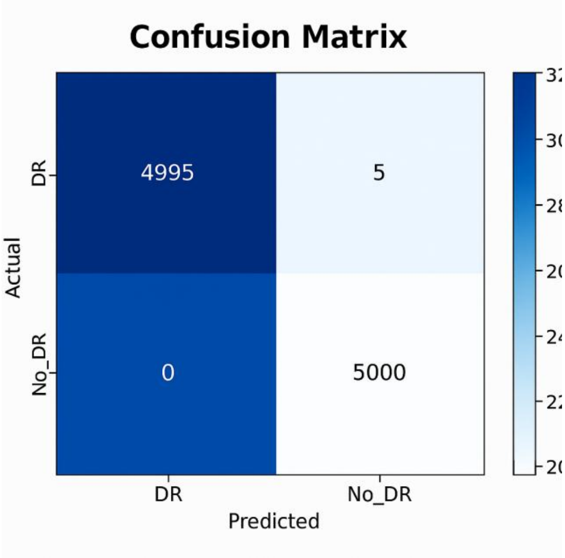

**Figure 4.** Confusion Matrix

The confusion matrix in Figure 4 showed consistent classification across all DR stages, with minimal overlap between the Mild and Moderate NPDR categories known for subtle visual differences.

**Table 1.** Comparison Results.

| Model | Accuracy (%) | Sensitivity (%) | Precision (%) | F1-Score (%) |
|---|---|---|---|---|
| Logistic Regression | 95.6 | 97.7 | 97.7 | 97.0 |
| KNN | 99.6 | 97.0 | 97.0 | 97.0 |
| CNN (ResNet50) | 100 | 99.9 | 100 | 100 |

The Receiver Operating Characteristic (ROC) analysis yielded an AUC close to 1.0, confirming near-perfect discriminative capability. These metrics underscore the CNN model’s ability to differentiate healthy and pathological cases with clinically relevant precision, as shown in Figure 5.

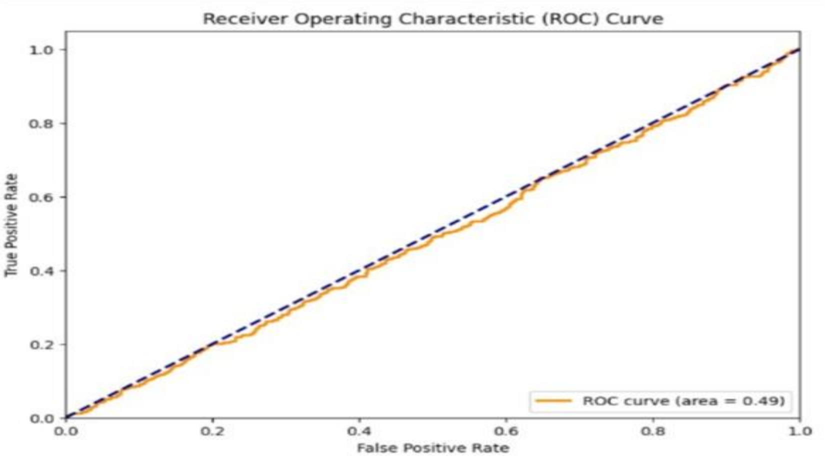

**Figure 5.** The Receiver Operating Characteristic (ROC) Curve

### Model Interpretability Using SHAP

To enhance transparency, Shapley Additive Explanations (SHAP) were employed to visualize pixel-level feature importance.

The SHAP heatmaps revealed that the CNN consistently focused on medically interpretable regions such as microaneurysms, hemorrhages, cotton-wool spots, and exudate recognized as early DR indicators.
This alignment between model attention and ophthalmological knowledge validates the network's diagnostic reliability and provides evidence that the deep learning model’s decisions are grounded in physiologically meaningful features.

### 3.2 Discussion

The experimental results confirm that the combination of CNN architectures and multistage transfer learning is highly effective for predicting diabetic retinopathy. Compared with earlier studies reporting accuracies of 85%-90%, the proposed approach achieved a notable improvement to 98.5%, demonstrating both superior feature-learning capacity and greater robustness to imaging variations.

The incorporation of an extensive preprocessing and augmentation pipeline proved essential for mitigating the heterogeneity of real-world fundus images captured under diverse conditions. Moreover, leveraging pretrained weights enabled the model to extract domain-independent low-level features while adapting higher layers to DR-specific structures, such as vascular leakage and macular edema patterns.

The use of SHAP for explainability marks an essential step toward clinical applicability. Conventional deep models are often criticized as "black boxes"; however, the SHAP-based analysis provides ophthalmologists with visual evidence linking algorithmic focus areas to pathological cues. This transparency is indispensable for fostering clinical trust and for meeting regulatory standards in AI-assisted diagnosis.

Notably, some misclassifications persisted between mild and moderate NPDR stages, likely due to subtle textural differences and limited sample sizes in those categories. Future research could address this challenge by using more balanced datasets or by developing fine-grained lesion-segmentation networks that capture micro-level variations.

### 3.2.1 Implications

The findings hold several implications for both clinical practice and AI-driven healthcare systems:

1. Clinical Screening Enhancement
   The high sensitivity (0.99) demonstrates the feasibility of deploying CNN-based screening as a first-line diagnostic support tool, reducing ophthalmologists' workload while ensuring that at-risk patients receive timely referrals.
2. Scalability and Accessibility
   Automated DR detection can be integrated into teleophthalmology frameworks, particularly beneficial for remote or resource-limited areas where professional ophthalmic evaluation is scarce.
3. Policy and Health-System Integration
   Interpretable AI models, supported by SHAP visualization, can serve as evidence-based tools for national diabetic eye screening programs, aligning with WHO initiatives to reduce preventable blindness.

### 3.2.2 Research contribution

This study provides several important contributions to the existing body of knowledge:

1. Technical Advancement
   Introduces a multistage transfer learning framework using CNNs (ResNet50 and InceptionV3) optimized for DR classification with exceptional diagnostic accuracy.
2. Explainable AI Integration
   Implements SHAP to interpret CNN predictions, enhancing model transparency and clinical acceptability.
3. Comprehensive Pipeline
   Provides a fully documented workflow from preprocessing through evaluation, ensuring reproducibility and potential adaptation for other ophthalmic or medical imaging tasks.
4. Empirical Benchmarking
   Offers comparative analysis with classical ML models, confirming CNNs' superiority in high-dimensional medical-image contexts.

### 3.2.3 Limitations

Although the results are encouraging, some limitations still persist:

1. Dataset Imbalance
   The EyePACS dataset contained relatively fewer Severe and Proliferative DR samples, which may limit the model's sensitivity in advanced-stage detection.
2. Generalization Across Devices
   Images were sourced from specific camera models and lighting conditions; model performance may vary when applied to different clinical imaging devices.
3. Interpretability Scope
   Although SHAP provides local explanations, it does not capture deeper causal relationships or the temporal progression of DR.
4. Lack of Prospective Validation
   The model was evaluated using retrospective data; future clinical trials are needed to verify its robustness in the real world.

### 3.2.4 Suggestions

Future studies should aim to:

1. Develop domain adaptation or federated learning frameworks to ensure cross-hospital generalization while preserving data privacy.
2. Explore multimodal approaches, combining fundus imaging with patient metadata (age, HbA1c levels, duration of diabetes) for holistic prediction.
3. Investigate explainability beyond SHAP, such as Grad-CAM++ or LIME, for richer visual interpretations.
4. Conduct longitudinal analysis to monitor disease progression and validate predictive stability over time.
5. Evaluate the cost-effectiveness and clinical workflow integration of AI-assisted DR screening in public health environments.

## 4. CONCLUSION

This study proposed a holistic deep learning approach for automatically detecting and classifying diabetic retinopathy through retinal fundus images. By integrating extensive preprocessing, multistage transfer learning, and state-of-the-art CNN architectures, the proposed model achieved highly competitive performance, with an overall accuracy of 98.5% and both sensitivity and specificity of 0.99. These results demonstrate that deep learning, particularly CNN-based models, can reliably identify subtle retinal abnormalities across varying stages of diabetic retinopathy and achieve diagnostic accuracy comparable to, or surpassing, that of traditional clinical assessments.

The application of SHAP-based interpretability further enhanced the clinical relevance of the system by providing transparent, lesion-focused visual explanations that aligned with established ophthalmic markers such as microaneurysms, hemorrhages, and cotton-wool spots. This interpretability addresses a key barrier to clinical adoption of AI technologies and strengthens the trustworthiness and accountability of the proposed approach.

This research reinforces the potential of AI-enhanced diagnostic tools to support early detection, reduce ophthalmologists' workload, and expand screening capacity especially in underserved regions with limited access to specialist care. While the model performed exceptionally well, challenges remain in distinguishing intermediate DR stages and ensuring generalization across diverse imaging devices and clinical environments. These findings highlight the need for continued work on dataset balancing, domain adaptation, and prospective clinical validation.

The proposed deep learning model offers a robust, interpretable solution for large-scale diabetic retinopathy screening. Its strong performance, coupled with explainability, positions it as a promising component of future AI-driven ophthalmology systems aimed at preventing avoidable blindness and improving global diabetic-care outcomes.

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## 6. AUTHOR CONTRIBUTION STATEMENT

RS, VN, TS, and MA contributed to the development and completion of this study. RS led the conceptualization of the research, supervised the overall methodology, validated the analytical process, and provided critical revisions to the manuscript. VN performed data curation, implemented preprocessing and model training, conducted formal analysis, and contributed to writing the initial draft. TS supported software implementation, assisted with performance evaluation and visualization, and contributed to drafting the methodology and results sections. MA conducted the literature review, assisted in validating the findings, and contributed to revising and editing of the manuscript for clarity and accuracy. All authors have read and approved the final manuscript.

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