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Study On Of Diabetic Retinopath Using Mahcine Learning Algorithms

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ABSTRACT
Diabetes mellitus (DM) is a metabolic disorder characterized by elevated blood glucose levels due to insufficient insulin production or a diminished response to insulin. Symptoms include "sweet urine"(glucosuria) and muscle wasting, which are direct consequences of uncontrolled blood glucose levels. Diabetic complications can significantly affect individual health outcomes, leading to elevated healthcare costs and potentially reducing overall life expectancy. The prevalence of diabetes is increasing worldwide, with projections predicting a rise from 2.8% in 2000 to 4.4% by 2030. The incidence of diabetes diagnoses is expected to increase from 171 million in 2000 to 366 million by 2030. Although men are more likely to develop diabetes, a larger proportion of women are now being diagnosed. The prevalence of diabetes is expected to increase threefold in urban populations of developing countries from 2000 to 2030. The primary demographic variable influencing global diabetes prevalence is the increasing population of individuals aged 65 and above. India has the highest prevalence of diabetes globally, with 50.8 million individuals diagnosed in 2009. China follows with 43.2 million, while the United States stands at 26.8 million.
KEYWORDS: *Diabetes mellitus (DM), diabetic retinopathy, RNN and CNN.*

I. INTRODUCTION

Efficient data preparation is bedrock of improving picture quality in machine learning models without sacrificing computing performance. Artefacts such as noise, poor contrast, and fluctuations in brightness are common in fundus pictures used to detect diabetic retinopathy. Addressing these problems and improving their applicability for training applications requires preprocessing of fundus pictures. After preprocessed fundus pictures are prepared for analysis, next stages include removing blood vessels, reducing noise, enhancing contrast, and selecting channels to identify possible lesions. original RGB color model consisting of main hues red, green, and blue was used to create color fundus pictures. red channel is quite saturated, blue channel is very dark, and green channel is best at seeing retinal backdrop and blood vessels. only thing that makes boats more visible is verdant river. We will focus our attention on channel with highest green-spectrum contrast for further research. Pretreatment methods are crucial for optimizing retinal image processing because they reduce noise that is created during picture capture and analog-to-digital conversion. Since noise has a major influence on fundus retinal vision and might cause misunderstandings, effective noise reduction is critical. This study encompasses techniques such as feature extraction, categorization, and preprocessing. Median filters effectively mitigate noise while preserving edge integrity, particularly after processes such as color space transformation and zero padding. main goal of this initiative is to improve precision and dependability of diabetic retinopathy (DR) databases. This document introduces an innovative methodology for pre-processing of datasets to attain defined objective. It is essential to consider metrics such as specificity, sensitivity, classification accuracy, F-measure, and precision when evaluating and comparing established methodologies. assessment methodology employs several benchmark datasets, such as MESSIDOR, IDRID, and APTOS. results indicate that proposed hybrid algorithm demonstrated a substantial performance advantage over alternative methods.

The green channel is extracted, contrast is increased, and Wiener filtering is used to early pre-processing steps of fundus camera images [74]. After picture has been pre-processed, it is subjected to morphological processing in order to improve identification of retinal blood vessels. To accurately demarcate lesions like microaneurysms, hemorrhages, and exudates, produced picture is subjected to graph cut segmentation. Among many statistical metrics that may be retrieved from segmented picture, two notable examples of texture descriptors are grey level dependency matrix and histogram of orientated gradients (HOG). We use retrieved features to train CRF classifier. During testing, classifier identifies DR lesion and assesses its severity. Metrics like sensitivity, accuracy, and specificity are used to quantify performance indicators.

II. BACKGROUND WORK

This chapter discusses the literature on image processing and data mining methods applied to retinal image analysis in the detection of Diabetic Retinopathy (DR). Retinal image analysis involves identifying different structural and disease patterns, such as macular and fovea, blood vessels, and optic discs. Image classification is a method of categorizing objects in an image or entire image into classes using an analytical approach. Current classification methods heavily rely on feature extraction and classifiers, with the goal of improving classification accuracy.

[1] conducted an investigation into creating trustworthy diabetic retinopathy predicting algorithms using various approaches, including Decision Trees, Bagging, Adaptive Boosting, Random Forests, and proposed Support Vector Machine with a Gaussian kernel. They found a maximum accuracy of 81.3% for this model throughout the experiment. [2] used ensemble learning approaches to assess six decision tree-based classifiers, including Adaptive Boosting (AdaBoost) and bagging with Naive Bayes classifier, with impressive results showing a 98.65% accuracy rate. [3] focused on prediction approaches for diabetic retinopathy using a dataset marked by high dimensionality and a restricted sample size. They created a Sels stacking model that achieved a classification accuracy of 83.95% compared to the suggested prediction model. [4] created a feature-based approach that outperformed all other models in properly predicting diabetic retinal system traits, reaching a level of accuracy of 0.975. The essay compares and contrasts traditional approaches with machine learning techniques, focusing on the Adaptive Boosting classifier for identifying and categorizing exudates based on pre-existing criteria. [5] presented a healthcare data-centric system using supervised machine learning approaches, with boosted trees outperforming individual trees by F-Scores of 97.8% and bagged trees by 97.6%.

Firefly dimensionality reduction and principal component analysis (PCA) are two common approaches to feature extraction and dimensionality reduction, respectively, with a 96% accuracy rate. Keerthiveena et al. assessed the effectiveness of Firefly algorithm in detecting diabetic retinopathy in their 2019 study, which used directional signals to separate filters in blood arteries of varying widths. [6] developed a comprehensive strategy using multiple classification algorithms for diabetic retinopathy identification, with an ensemble-based model achieving a classification accuracy of 96.34%. [7] investigated a novel machine learning method to enhance early detection and classification of exudate photos, achieving 98% accuracy in color fundus pictures. [8] developed a model for predicting diabetic retinopathy using various methodologies, with the Support Vector Machine with Gaussian kernel being used as the initial strategy. [9] examined various machine learning techniques for DR classification, with XGBoost outperforming all other ML classifiers in terms of performance. [10] developed hybrid inductive ML algorithms for reliable DR screening, with pre-processing, segmentation, feature extraction, and multiple instance learning (MIL) components achieving better classification accuracy of 96.62%.

[11] designed a model for classification by identifying significant attributes, employing various feature selection strategies to extract feature subsets. [12] analysed different feature selection techniques, using Random Forest for classification, which achieved 69% of AUC. [13] investigated a unique method for classifying diabetes mellitus based on its features, with Random Forest achieving the highest accuracy of 79.8% of all classifiers. Piotr Chudzika et al. investigated "Microaneurysm Detection Using Fully Convolutional Neural Networks," which includes preprocessing, patch extraction, and pixel-wise categorization. CNN model datasets were used in experiments, resulting in maximum sensitivity at lowest false positive rates.

III. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

This study proposes a comprehensive approach for the early detection of glaucoma to mitigate its effects on the optic nerve head. Instrumental feature analysis is a component of the proposed methodology, which also accounts for other significant risk factors associated with glaucoma. The findings indicate that the used procedures were very successful and satisfied all criteria. study findings indicate that it can detect glaucoma with the same accuracy as human physicians using similar original study photographs. Evaluating the accuracy, velocity, and specificity of the proposed system

The true positive rate (TP) is the quantity of glaucomatous images accurately recognised by the proposed classifier. The quantity of standard images that the suggested classifier accurately recognised as typical instances is measured by the TN rate. The false positive rate is the quantity of healthy images that the suggested classifier erroneously categorises as glaucomatous. A false negative (FN) occurs when a classifier erroneously categorises glaucomatous images as normal.

Methodologies	Specificity (%)	Accuracy (%)	Kappa index (%)	Sensitivity (%)
Auto-encoder	88.4	92	85.45	91.77
RNN	76.55	72.03	86	72.33
LSTM	83	87.33	79.86	86.95
Proposed CNN	**97.49**	**96.89**	**88**	**97.34**

During initial analysis of dataset for a comprehensive overview of performance metrics of predicted model: sensitivity at 97.34%, specificity at 97.49%, and a kappa index of 88%. Conversely, contemporary techniques such as RNN, LSTM, and auto-encoder exhibit a kappa index ranging from 79% to 86%, specificity levels between 76% and 88%, sensitivity metrics between 72% and 91%, and accuracy percentages from 72% to 92%. This indicates that, in comparison to earlier methodologies, convolutional neural networks demonstrated superior performance in diabetic retinopathy prediction. visual analysis of predicted model across various performance criteria is illustrated in belowFigures , which classify images from MESSIDOR dataset.

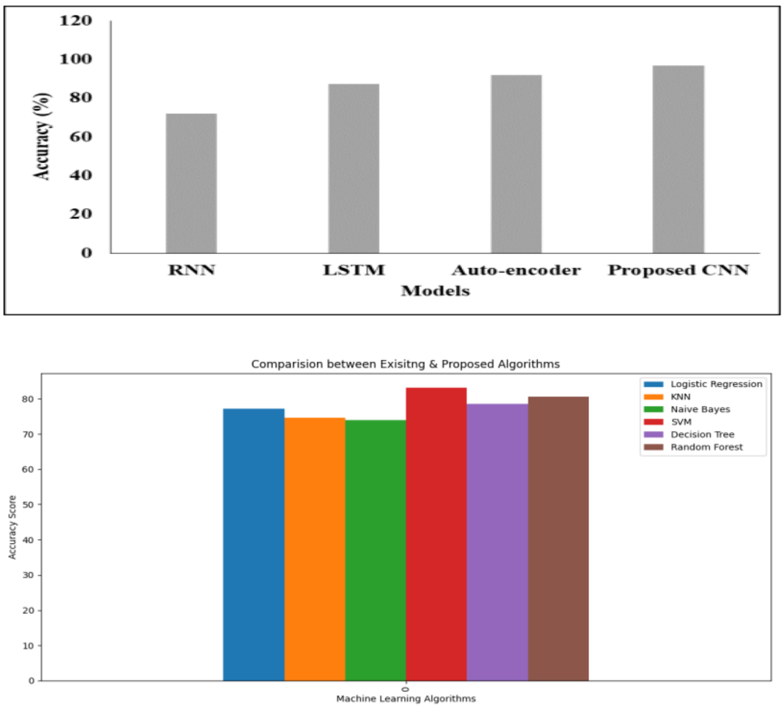

Figure 1 Comparison of different classifiers on metric Accuracy – MESSIDOR dataset

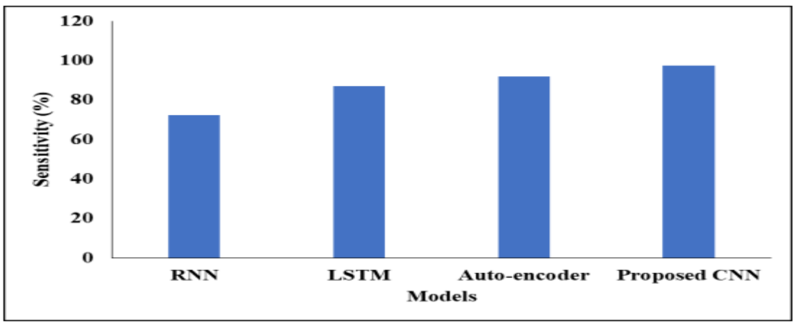

Figure 2 Comparison of different classifiers on metric Sensitivity – MESSIDOR dataset

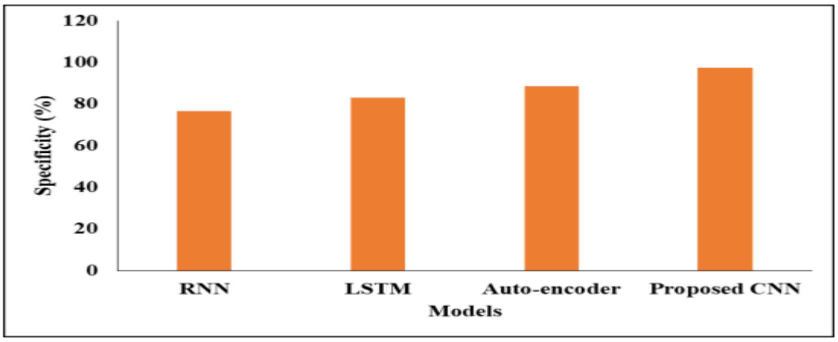

Figure 3 Comparison of different classifiers on metric Specificity – MESSIDOR dataset

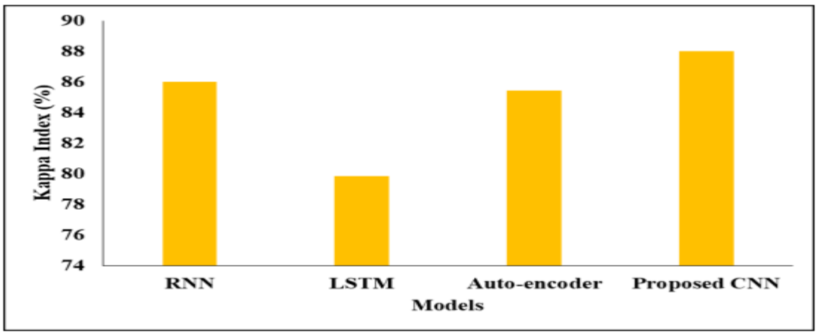

Figure 4 Comparison of different classifiers on metric Kappa Index – MESSIDOR dataset

Methodologies	Sensitivity (%)	Accuracy (%)	Specificity (%)	Kappa index (%)
RNN	85.43	91.22	75	79
LSTM	89	90.89	83.50	79.08
Auto-encoder	94.76	93.98	87	83.44
Proposed CNN	**97.12**	**97.43**	**98.09**	**89.67**

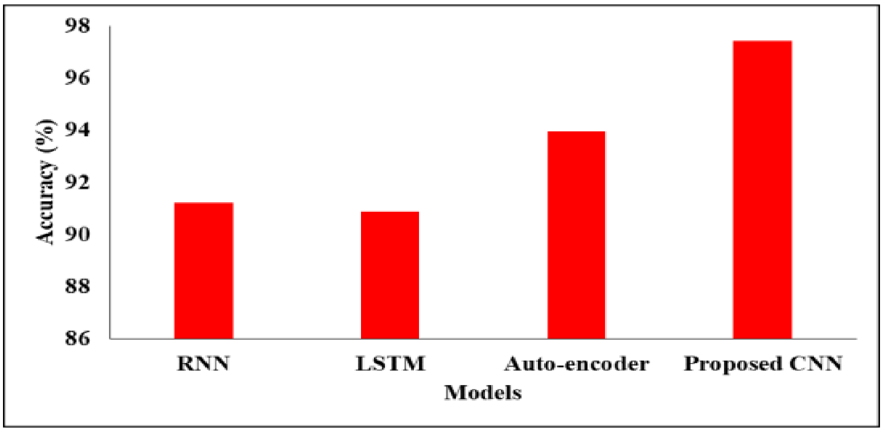

Figure 5 Comparison of different classifiers on metric Accuracy – IDRiD dataset

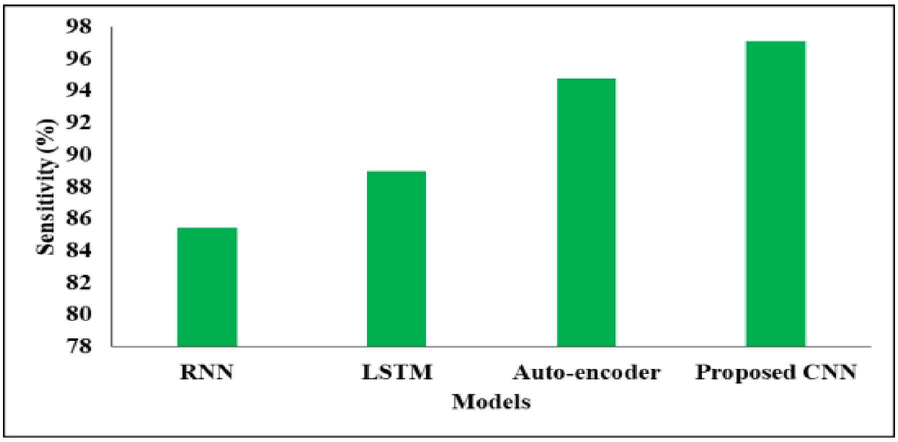

Figure 6 Comparison of different classifiers on metric Sensitivity – IDRiD dataset

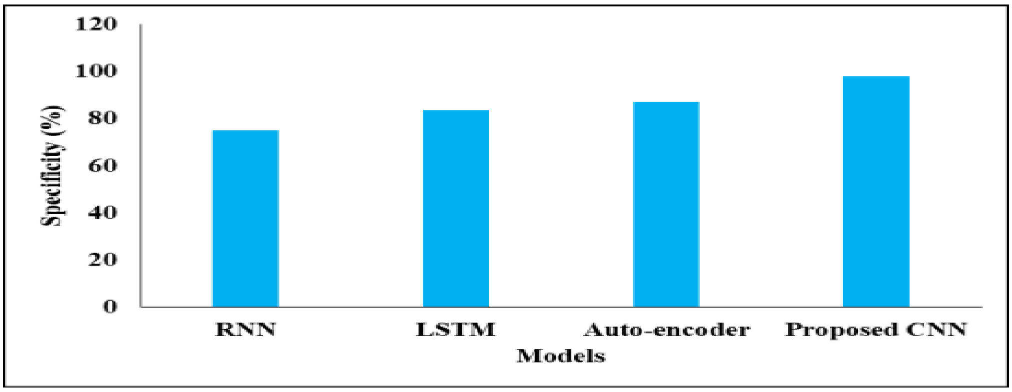

Figure 7 Comparison of different classifiers on metric Specificity –IDRiD dataset

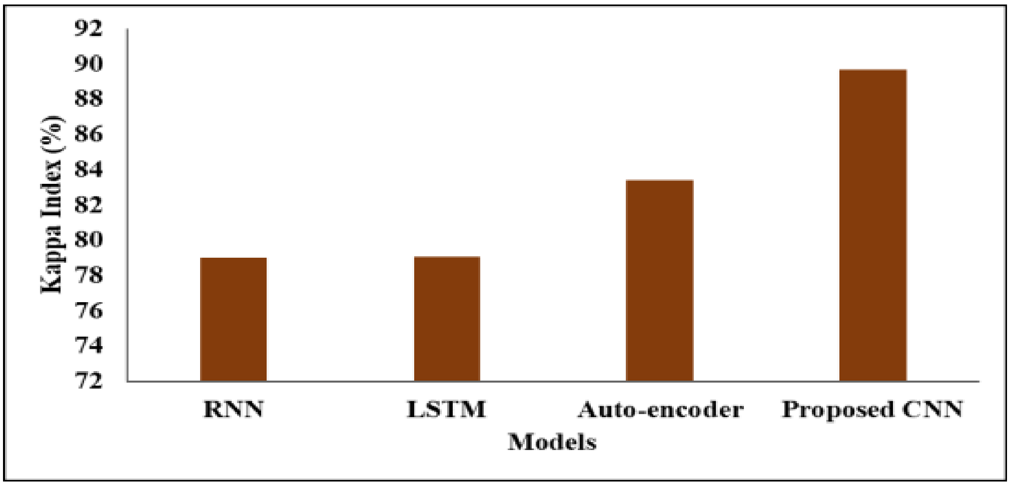

Figure 8 Comparison of different classifiers on metric Kappa Index – IDRiD dataset

Compared to achieved an accuracy of 91.22%, while LSTM model scored 90.89%, auto-encoder achieved an accuracy of 93.98%, while convolutional neural network (CNN) model achieved highest accuracy of 97.43%. During sensitivity testing, following results were documented: RNN obtained 85.43%, LSTM obtained 89%, auto-encoder got 94.76%, and CNN achieved 97.12%. In accordance with specificity studies, models were able to reach following performance metrics: RNN at 75%, LSTM at 83.50%, auto-encoder at 87%, and CNN at 98.09%. In contrast to other evaluation methods, results of Kappa index analysis indicate that RNN scored 79%, LSTM scored 79.08%, auto-encoder scored 83.44%, and CNN model earned highest at 89.67%. These results indicate that RNN, LSTM, and auto-encoder models all performed poorly.

IV. CONCLUSION

Early detection of glaucoma is crucial as it can cause permanent vision loss if left untreated. Research on three-dimensional imaging reveals structural abnormalities in the optic nerve head and retinal nerve fiber layer, leading to visual field limitations. However, subjective criteria have led to variability in evaluation. Recent studies have linked an enlarged optic disc to a higher likelihood of developing glaucoma. Optic nerve head (ONH) undergoes morphological alterations and nerve fiber atrophy due to convergence of optic nerve fibers. Adaptive histogram equalization converts color images to greyscale, and the process of creating Tetons involves extracting features from greyscale images using color and texture descriptors. Sequential forward search and t-test make feature selection and ranking easier. Several classifiers have large parameters to differentiate between different classifiers. The novel approach, LS-LVM, outperforms traditional approaches, achieving a 99% accuracy rate. HCTFV outputs 91.67% when using DC, 94.16% when using RF, and 96.67% when using SVM.

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