

Glaucoma Detection Using Hybrid Machine Learning Techniques

¹Suleiman Salihu Jauro, ^{2*}Sulaiman Yusuf Ali, ³Muhammed Kabir Ahmed

¹Department of Computer Science,
Faculty of Science,
Gombe State University,
Nigeria.

²Department of Computer Science,
School of Science,
Federal Polytechnic Kaltungo,
Gombe State,
Nigeria.

³Department of Computer Science,
Faculty of Science,
Gombe State University,
Nigeria

Email: yusufsulaiman766@gmail.com

Abstract

An eye disease called glaucoma can cause irreversible blindness if left undetected and not properly managed. The major challenge is that glaucoma often has no symptoms in its early stages, making it hard to detect using traditional testing methods like eye pressure measurements and eye exams. Several techniques for Glaucoma detection encountered difficulties due to a short training dataset, resulting in overfitting and under fitting problems. A hybrid machine learning approach based on CNN-SVM for detection of Glaucoma was proposed. Initially images taken from glaucoma dataset were preprocessed using standard scalar, then the preprocessed images are fed into CNN for transformation into high level features, the extracted features are subsequently passed onto an SVM classifier to distinguish between normal and glaucomatous conditions. Experimental results for the proposed CNN-SVM offers an accuracy, precision, recall and F1-score of 100% demonstrating its superiority over other existing techniques such as SVM which has accuracy, precision, recall and F1-score of 93%, 92%, 90% and 94% respectively and CNN with the accuracy, precision, recall and F1- score of 95%, 99%, 88% and 90% respectively. The integration of CNN and SVM presents a promising framework for automated Glaucoma detection, offering significant potential for real-world clinical applications.

Keywords: Hybrid machine Learning Technique, Glaucoma detection, CNN, SVM, CNN-SVM

INTRODUCTION

The body of humans has a total of five senses: contact, sight, sound, scent, and taste; however, sight is one of the most commonly employed. Processing visual information takes a lot of brain power (Guangzhou et al., 2019). Glaucoma, diabetic retinopathy, cataracts, amblyopia, refractive mistakes, and age-related macular degeneration are some of the disorders that can

cause visual loss. Glaucoma is the second most common cause of blindness worldwide (Guo *et al.*, 2020). It can cause irreversible sight loss in a few years and deteriorate with time (Tham *et al.*, 2014). Despite the lack of evident indicators of pain or reduced vision, the global population of individuals with Glaucoma is anticipated to increase by 74% by 2040, reaching 111.8 million (Tham *et al.*, 2014).

Glaucoma is an eye illness that affects the optic nerve, which is necessary for vision. The primary problem is that Glaucoma frequently has no symptoms in its early stages, making it difficult to identify using typical diagnostic procedures such as ocular pressure readings and eye examinations (Miller *et al.*, 2023). By the time vision difficulties emerge, the optic nerve may have already suffered severe damage (Wang *et al.*, 2023). As glaucoma rates rise internationally, late detection and treatment can have a significant impact on patients' quality of life, raise healthcare expenses, and burden society (Ozcelik-Kose *et al.*, 2022). Recent research looked into the use of machine learning algorithms to diagnose glaucoma in its early stages.

Machine learning has become an indispensable instrument in the field of glaucoma diagnosis and treatment, providing a wide range of applications in many care domains. It has been useful in assessing treatment results, forecasting the course of disease, interpreting clinical data, and analyzing imaging investigations like optical coherence tomography (OCT) images. Large volumes of data may be processed quickly by these algorithms, and they frequently outperform human practitioners in some glaucoma diagnostic and monitoring tasks. In this paper the existing methods for glaucoma detection were investigated which are as follows: recommended that the identification of glaucoma is an essential component of medical study, as it may have consequences for permanent blindness. The Inception V3 model, a CNN-based technique, was utilized to develop a cheap glaucoma detection model that overcomes the limitations of traditional diagnosis. The model outperformed the DenseNet121 and ResNet50 algorithms, with an accuracy of 0.8529 and an AUC of 0.9387. However, further clinical validation is required for broader applications (Afroze *et al.*, 2021).

Study by (Alqarni *et al.*, 2024) presents a novel approach for early glaucoma detection using Convolutional Neural Networks (CNNs) with pixel-wise attention. The work describes a new method for diagnosing healthy or glaucomatous eyes that employs optic disc extraction and retinal image categorization. When compared to previous methods, the method provides much higher accuracy, sensitivity, and specificity. It establishes a new standard for ROC curve area under the curve and accurate localization. The CNN-based technique attained an outstanding accuracy of 98.9%. and also a study by (Oguz, *et al.*, 2024) presents a novel approach to detecting glaucoma using a hybrid model that combines Deep Learning (DL) and traditional Machine Learning (ML) techniques. This study employs raw fundus images to extract deep information via a novel Convolutional Neural Networks model. These characteristics are then classified using popular machine learning techniques as Adaboost, KNN, RF, Multilayer Perceptron, SMV, and Naive Bayes. CNN-Adaboost hybrid model has the highest success rate, with 92.96% accuracy, 93.75% F1 score, and an AUC of 0.928.

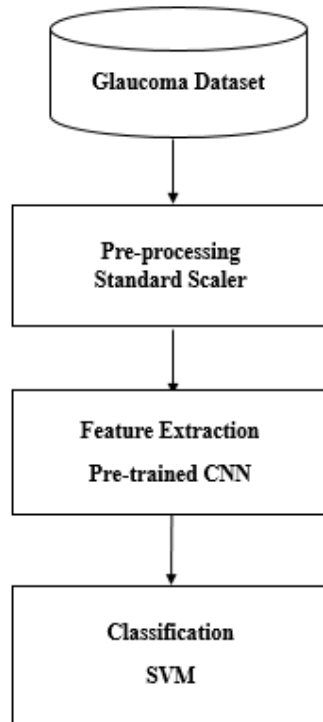
Propose an advanced computerized system that integrates machine learning (ML), convolutional neural networks (CNNs), and image processing for accurate glaucoma detection using medical imaging data. To assess preprocessed retinal pictures, the authors created a hybrid architecture that includes ResNet50 and VGG-16 CNNs, as well as a Random Forest model. Texture features are derived from fundus phantasmagorias using the Gray-Level Co-Occurrence Matrix method. The model obtained 95.41% accuracy, with 99.37% precision and 88.37% recall (Aljohani and Aburasain, 2024). Presented a machine learning

approach for detecting glaucoma, an eye disease that can cause blindness, using retinal fundus images. The authors suggested an efficient approach for early glaucoma detection that includes Data collection, image processing, feature extraction, model training, and deployment. They employed a number of machine learning models, including LR, SVM, RF, Naive Bayes, and Decision Tree, with Logistic Regression model achieving the greatest accuracy of almost 95% on test data (Yerragudipadu *et al.*, 2024).

METHODOLOGY

Proposed framework

The glaucoma dataset used in this study is a secondary dataset that was obtained from Kaggle. The dataset underwent pre-processing as a cleaning technique to ensure accurate and reliable results. The data was divided into seventy percent for training and thirty percent for testing to evaluate model performance. Feature extraction was performed using convolutional neural networks (CNN) to identify essential features, which were then classified with support vector machine (SVM) because of its effectiveness and also high classification accuracy. The classification task aimed to categorize eye images as either glaucoma or non-glaucoma. Model Metrics like as accuracy, precision, recall, F1-score, and ROC were used to assess the hybrid model's reliability and usefulness in detecting glaucoma.



Framework of the proposed hybrid CNN-SVM Model

Pre-processing

This study employed pre-processing techniques which is referred to as standard scaler. Each feature is separately centered and scaled using the useful values within instruction set's samples. Standard deviation and mean subsequently used to edit more data later. Several machine learning estimators need dataset normalization; else they will accomplish badly If each of the features are not closely related to conventional normally distributed data.

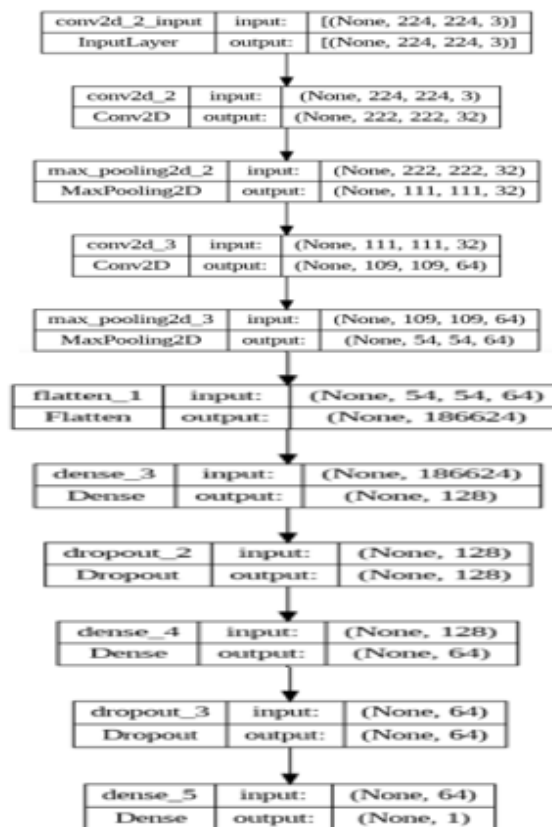
Class sklearn. pre-processing the StandardScaler (*, copy=True, with_mean=True, with_std=True): Standardizes characteristics by removing a mean and growing to unit variance. The standard score of a sample (x) is calculated as follows:

$$z = (x - u)/s$$

In this equation, u represents the mean of the training samples (or zero if with_mean=False) and s represents the standard deviation (or one if with_std=False).

Feature Extraction using CNN

The feature extraction techniques used for this study referred to as Convolutional Neural Network (CNN). CNNs are predominantly powerful for tasks correlated to computer vision, where the goal is to recognize and understand visual patterns within input data. The main mechanisms of a CNN comprise convolutional layers, pooling layers, and fully connected layers. below represents a clear graphical representation of the CNN model's architecture, which helped in understanding the structure and flow of data through the process. Detail explanation of the layers of the model is found below.



CNN Architecture of the Proposed Model

- i. **Conv2D (32 riddles, 3x3 kernel, ReLU activation):** This the initial convolutional layer with 32 3x3 sifters and ReLU stimulation function. It processes the supplied picture with the form (224, 224, 3).
- ii. **MaxPooling2D (2x2 pool size):** The initial max-pooling level that diminishes spatial dimensions by a factor of two.
- iii. **Conv2D (64 filters, 3x3 kernel, ReLU activation):** The another convolutional stratum comprises of 64 3x3 riddles activated with ReLU function.
- iv. **MaxPooling2D (2x2 pool size):** The second max-pooling layer reduces spatial dimensions by using a pool size of 2x2.
- v. **Flatten:** Converts the yield from the forgoing stratum to a 1D vector.
- vi. **Dense (128 units, ReLU activation):** This layer is completely linked and has 128 units.

- vii. **Dropout (0.5 rate):** To prevent overfitting, utilize a waster layer with a rate of 0.5.
- viii. **Dense (64 units, ReLU activation):** This fully linked layer uses 64 units and ReLU stimulation to extract intermediate features.
- ix. **Dropout (0.5 rate):** Adds a waster layer with a rate of 0.5.
- x. **Dense (1 unit with Sigmoid activation):** The final output layer for binary classification consists of a sole unit and a sigmoid motivation task.

Classification using SVM

The classical SVM machine learning method is used for binary classification problems. In this work, an SVM identify retinal pictures as healthy or glaucoma-related based on visual attributes. Features extracted from the images could include statistical measures, texture descriptors, or other relevant characteristics. The SVM learns a decision boundary that split up the two periods of images in the feature space.

SVM is best designated in practice by referring to a conjectural classifier known as the Maximal-Margin Classifier. The geometric input variables (x) in the facts (columns) define n-dimensional cosmos. Hyperplane is line that divides space of input variables. SVM, the hyperplane is chosen optimally segregate points in input variable space by class, which may be either 0 or 1. In n dimensions, say two, you may view this as a line that separates all of our input points.

$$B0 + (B1 * X1) + (B2 * X2) = 0$$

The erudition process determines the slope (B1 and B2) and intercept (B0), whereas X1 and X2 are the input variables. You can use this line to classify things. By entering input values into the line equation, you may determine if a new point is above or below the line.

Hybrid CNN-SVM Model

A hybrid CNN-SVM model for glaucoma diagnosis combines the advantages of convolutional neural networks (CNN) with support vector machines (SVMs). In this method, the CNN extracts high-level features from retinal pictures, collecting complex information related to glaucoma, and the SVM classifies these features as glaucomatous or non-glaucomatous. This combination increases accuracy, decreases overfitting, and improves generalization when compared to a single model. However, it necessitates precise adjustment and large processing resources. The hybrid approach shows promise for clinical applications, including real-time glaucoma diagnosis and integration with other techniques for future developments.

Performance Metrics

Performance indicators examine how effectively the model distinguishes between glaucomatous and healthy retinal pictures. Several performance measures are calculated to assess the model's performance. Communal metrics for binary classification tasks like glaucoma detection are:

Accuracy

Determines how often a model properly predicts the result. It is the ratio of the model's correct predictions to its overall forecasts.

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn}$$

Precision

Measures quality of a positive prediction made by the model.

$$Precision = \frac{tp}{tp + fp}$$

Recall (Sensitivity)

The fraction of true positive forecasts to all actual positive cases. It assesses the model's ability to identify all positive cases. It is the amount of real positives divided by the total number of actual negatives.

$$Recall = \frac{tp}{tp + fn}$$

F1-Score

The mean of the harmonics of accuracy and recall achieves a balance between the two measurements.

$$F1 - Score = 2 \left(\frac{precision * recall}{precision + recall} \right)$$

RESULTS AND DISCUSSION

The proposed hybrid CNN-SVM model received perfect scores on all performance metrics, including 100.00% accuracy, precision, recall, and F1-score, demonstrating outstanding performance in glaucoma detection. These results show that the model effectively detected and generalized the characteristics that identify glaucomatous from normal pictures, which was most likely due to the dataset's complete training. The model's capacity to perform well across all performance criteria demonstrates its promise as a reliable glaucoma diagnostic tool. The performance metrics for the proposed hybrid convolutional neural network and support vector machine (CNN-SVM) glaucoma detection model are shown below.

Classification result

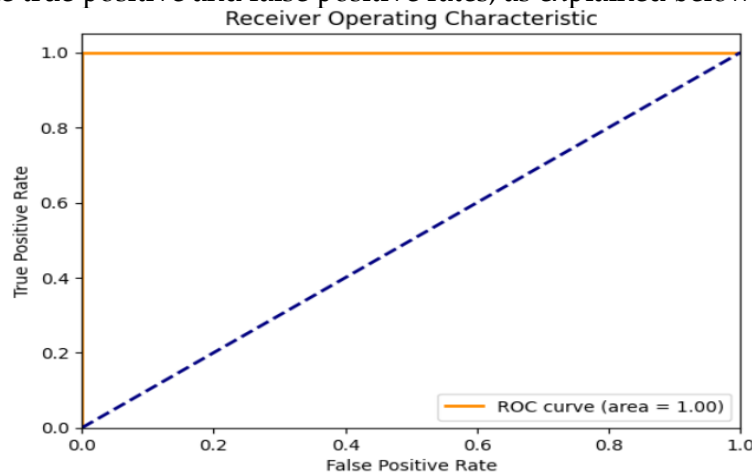
classification report tells overall how often the proposed model is correct. also see precision, recall, and F1 Score, which give insights on how well the proposed model is doing as shown below.

	precision	recall	f1-score	support
0.0	1.00	1.00	1.00	600
1.0	1.00	1.00	1.00	600
accuracy			1.00	1200
macro avg	1.00	1.00	1.00	1200
weighted avg	1.00	1.00	1.00	1200

Classification results of the proposed hybrid CNN-SVM

ROC

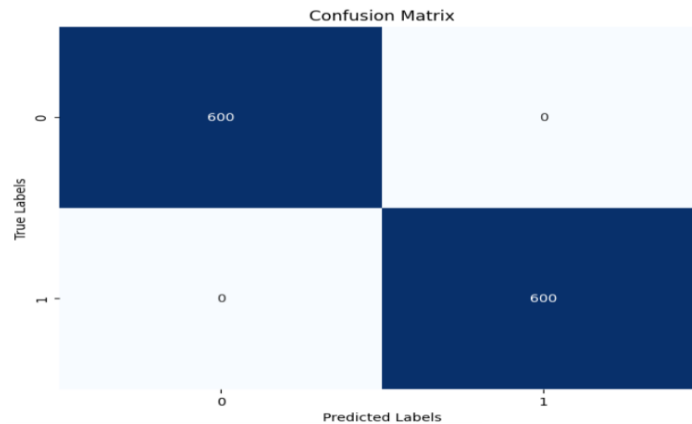
Receiver operating characteristics (ROC) curves are graphs that depict classifier performance by graphing the true positive and false positive rates, as explained below.



Receiver Operating Characteristics (ROC) of the proposed model

Confusion metrics

The confusion matrix for glaucoma diagnosis using hybrid CNN-SVM displays the total number of accurate and wrong predictions. With a true positive and false positive rate of 100% each, a true negative rate of 0%, and a false discovery rate of 0%. This technique is highly accurate due to the use of strong model feature extraction and classification, a convolutional neural network, and a support vector machine.



Confusion metrics of the proposed model

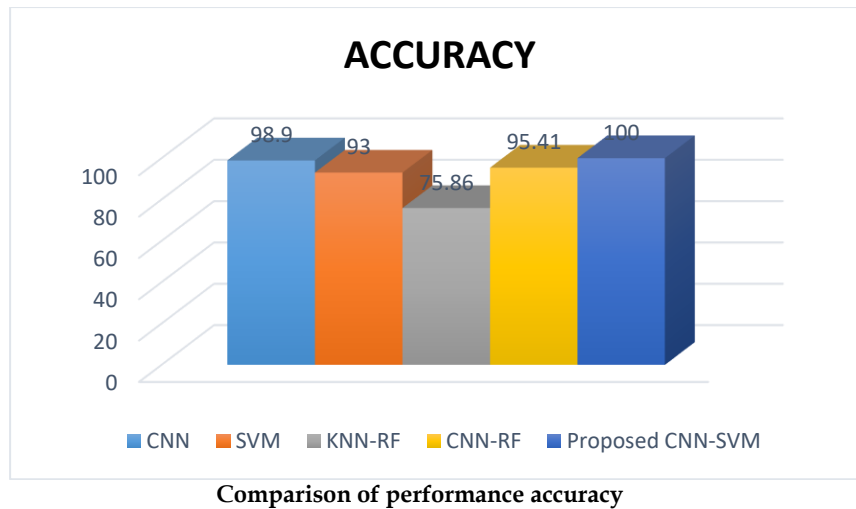
Comparison of proposed CNN-SVM with existing techniques

The proposed CNN-SVM and existing glaucoma detection approaches were compared using accuracy, precision, recall, and F1-score. The proposed CNN-SVM model, were tested achieved 100% accuracy across all measures, indicating higher performance and generalizability in comparison to the current studies. The table below summarizes the performance metrics of the proposed hybrid convolutional neural network and support vector machine (CNN-SVM) model for glaucoma detection is compared to other current works in the area. As shown below.

Techniques	Author	Accuracy	Precision	Recall	F1-Score
CNN	Alqarni <i>et al.</i> , (2024)	98.9	98.8	99.1	-
SVM	Wu <i>et.al.</i> (2022)	93.0	92.0	90.0	94.0
KNN-RF	Athalla <i>et al.</i> , (2022)	75.86	71.72	76.24	71.42
CNN-RF	Aljohani and Aburasain, (2024)	95.41	99.37	88.33	93.52
Hybrid CNN-SVM model	Proposed Model	100.00	100.00	100.00	100.00

Accuracy

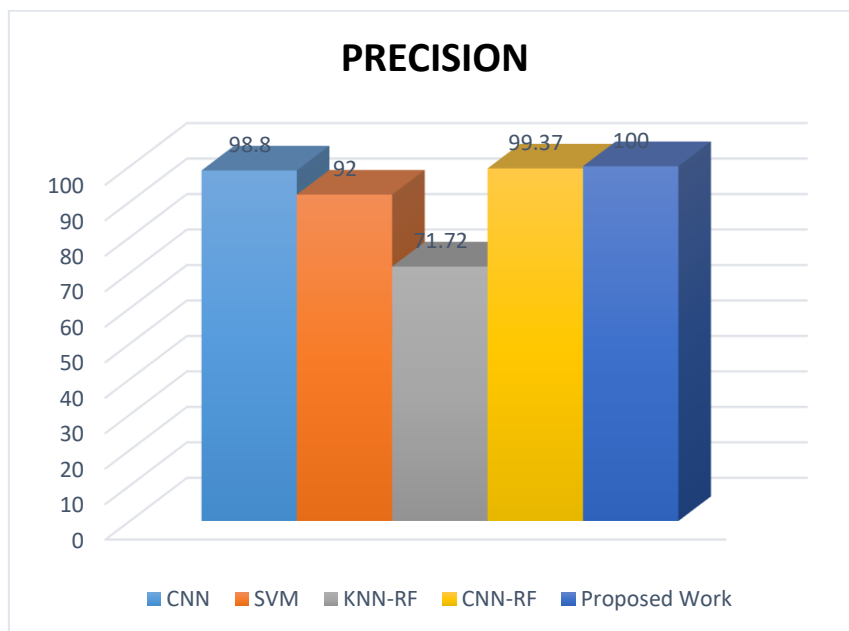
The proposed hybrid CNN-SVM model achieves perfect accuracy of 100%, which is a substantial advance above previous models. The hybrid CNN-SVM model superseded (Alqarni *et al.*, 2024), (Wu *et.al.* 2022), (Athalla *et al.*, 2022), (Aljohani and Aburasain, 2024) previous models in the literature, with accuracies of 75.86%, 95.41%, 93% and 98.9%, respectively. Achieving 100% accuracy means that the combination of CNN for feature extraction and SVM for classification resulted in perfect generalization and prediction on all instances. This result demonstrates the hybrid model's greater capacity to handle hard scenarios where other models have failed.



Comparison of performance accuracy

Precision

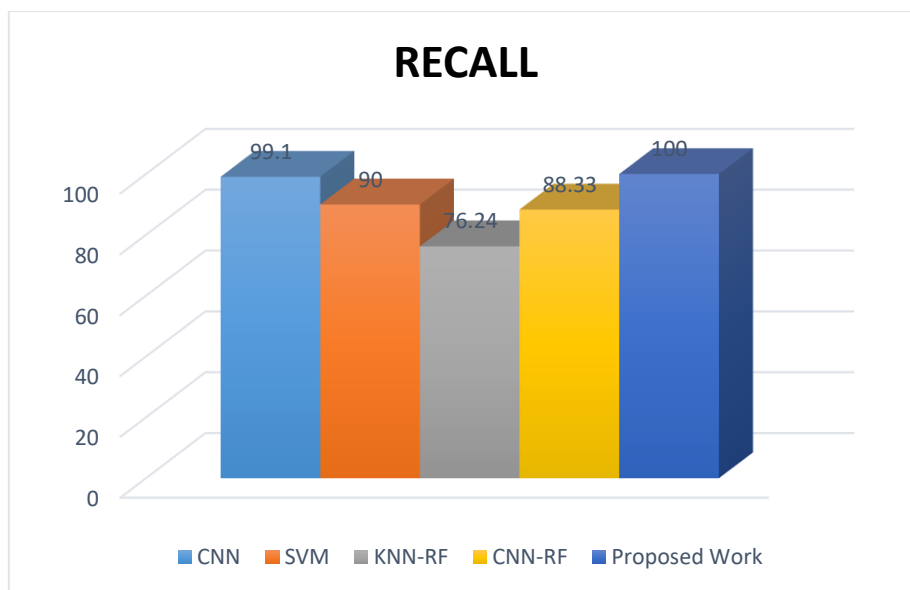
The proposed hybrid CNN-SVM model's 100% precision illustrates its unrivalled ability to correctly recognize true positives with no false positives, exceeding prior techniques. Other models in the literature such as (Alqarni *et al.*, 2024), (Wu *et.al.* 2022), (Athalla *et al.*, 2022), (Aljohani and Aburasain, 2024) have reported precision values of 71.5%, 85.5%, and 97.8% respectively showing various levels of effectiveness in avoiding false positives. The hybrid model's excellent accuracy and 100% precision demonstrate its exceptional capacity to detect true glaucoma cases, making it a highly reliable and accurate clinical diagnostic tool.



Comparison of performance precision

Recall

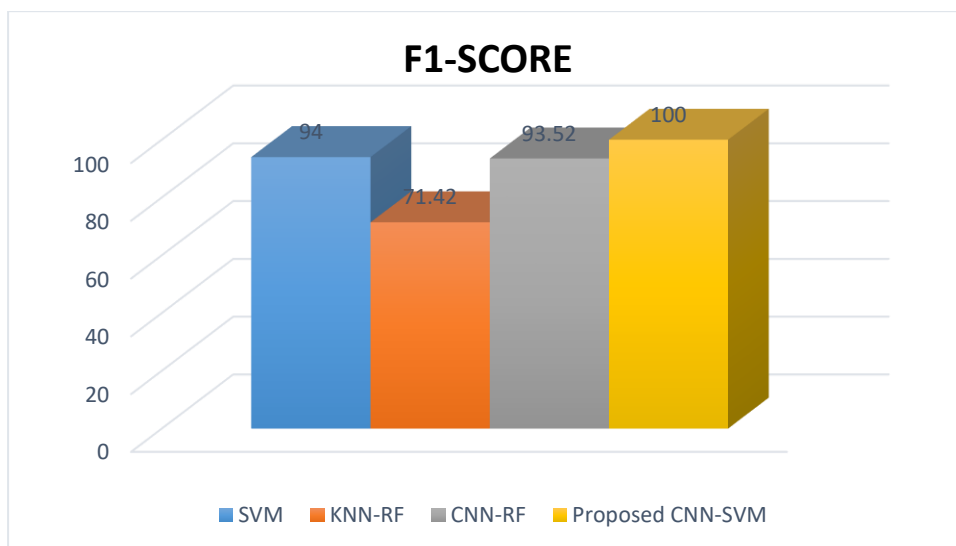
The proposed hybrid CNN-SVM model's excellent recall of 100% demonstrates its outstanding capacity to identify all genuine positive glaucoma cases without missing one. This performance is significantly better than earlier models which are (Alqarni *et al.*, 2024), (Wu *et.al.* 2022), (Athalla *et al.*, 2022), (Aljohani and Aburasain, 2024), which had recall rates of 99.1%, 76.24%, 88.33%, and 90% respectively. The hybrid model's faultless recall proves its dependability and efficacy in detecting every real case of glaucoma, outperforming previous models and stressing its increased diagnostic accuracy.



Comparison of performance recall

F1-Score

The proposed hybrid CNN-SVM model has a flawless F1-score of 100%, indicating remarkable performance in balancing accuracy and recall, making it very useful in diagnosing glaucoma. This differs from prior models, which obtained F1-scores of 71.42%, 94% and 93.52%, indicating a less ideal combination of accuracy and recall. The hybrid model's perfect F1-score displays its better ability to reliably detect genuine positives while reducing false positives and false negatives.



Comparison of performance f1-score

CONCLUSION

This study presents a hybrid CNN-SVM approach for glaucoma detection, demonstrating significant advancements in ophthalmic diagnostics. The model, which combines CNN's feature extraction capabilities with SVM's classification power, achieved 100% accuracy, precision, recall, and F1-score across all critical performance metrics. The system is highly effective in distinguishing between normal and glaucomatous retinas with exceptional accuracy. Comparative analysis with existing studies demonstrates the model's superiority, showing its robustness and generalizability on a larger dataset of 6000 images. This large

training dataset allowed the suggested model to learn a diverse set of characteristics, contributing to its perfect performance.

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