FOREX Publication
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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 2 | Pages 669-681 | e-ISSN: 2347-470X

CGSX Ensemble: An Integrative Machine Learning and Deep Learning Approach for Improved Diabetic Retinopathy Classification

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ABSTRACT- This research proposes an integrated approach for automated diabetic retinopathy (DR) diagnosis, leveraging a combination of machine learning and deep learning techniques to extract features and perform classification tasks effectively. Through preprocessing of retinal images to enhance features and mitigate noise, two distinct methodologies are employed: machine learning feature extraction, targeting texture features like Gray-Level Co-occurrence Matrix (GLCM) and Gray-Level Run Length Matrix (GLRLM), and deep learning feature extraction, utilizing pre-trained convolutional neural networks (CNNs) such as VGG, ResNet, or Inception. Following feature extraction, various classifiers, including Support Vector Machines (SVM), Random Forests, and Gradient Boosting Machines, are trained on the extracted features for DR classification. Alternatively, deep learning classifiers like CNNs or recurrent neural networks (RNNs) may be trained directly on the extracted features or on raw images. This comprehensive framework shows promising potential to improve the accuracy and efficiency of diabetic retinopathy (DR) diagnosis, enabling timely intervention and management of this vision-threatening condition.

General Terms: Deep Learning, Medical Image Processing.
Keywords: Diabetic Retinopathy, Feature Extraction, Machine Learning, Deep Learning, Classification.

ARTICLE INFORMATION
Author(s): K. Kayathri and Dr. K. Kavitha;
Received: 26/04/2024; **Accepted**: 11/06/2024; **Published**: 28/06/2024;
e-ISSN: 2347-470X;
Paper Id: IJEER 2604-30;
Citation: 10.37391/IJEER.120245
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-12/ijeer-120245.html

Publisher's Note: FOREX Publication stays neutral with regard to Jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

Diabetic retinopathy (DR) is a common complication of diabetes mellitus and continues to be a leading cause of blindness worldwide. This condition affects the retina, the light-sensitive tissue located at the back of the eye, and can result in vision impairment or complete loss of vision if not promptly treated. According to the World Health Organization (WHO), DR affects approximately one-third of people with diabetes, making it a significant public health concern.

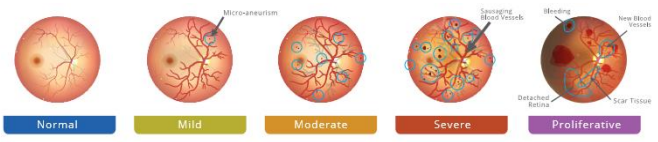

Figure 1. Diabetic Retinopathy: A Comparison of Stages

Table 1: Stages of Diabetic Retinopathy

Stage	Description
Normal	Healthy eye with a normal retina.
Mild	Early signs: microaneurysms (small bulges in blood vessels).
Moderate	More advanced signs: sausageing (wider blood vessels), hemorrhages (bleeding), exudates (new blood vessels).
Severe	Most advanced stage: severe retinal detachment and scar tissue. Significantly impairs vision.

Timely detection and precise classification of DR stages are essential for effective treatment and prevention of vision loss.

Timely intervention can help to slow the progression of the disease and mitigate its impact on vision. However, manual diagnosis of DR can be time-consuming and prone to subjectivity, leading to delays in treatment and suboptimal outcomes for patients [1].

In light of these challenges, there has been growing interest in leveraging artificial intelligence (AI) techniques, particularly Machine Learning (ML) and Deep Learning (DL), to automate the diagnosis of DR. These techniques have shown promise in extracting features from retinal images and classifying them into different stages of the disease, thereby streamlining the diagnostic process and improving patient outcomes.

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The aim of this study is to introduce an integrated method for automated diabetic retinopathy (DR) diagnosis using a combination of machine learning and deep learning techniques for effective feature extraction and classification. By harnessing the strengths of these methodologies, our goal is to create a robust and efficient system capable of accurately classifying DR stages from retinal images. This integrated approach holds significant promise in transforming the diagnosis and treatment of DR, ultimately enhancing the quality of life for millions impacted by this serious vision-related condition [2].

2. RELATED WORK

The work conducted by Lakshminarayanan et al. presents a thorough investigation into artificial intelligence (AI) methodologies applied to diabetic retinopathy (DR) detection and grading using ML and DL techniques. Their analysis covers studies published between 2016 and 2021, focusing on both fundus and optical coherence tomography (OCT) imaging modalities for retinal assessment. By leveraging ML and DL algorithms, researchers can extract features from images and identify signs of DR, assess its severity, and segment associated lesions. The review utilized systematic search strategies such as PICO and PRISMA to identify and summarize 114 relevant articles from the open literature. Additionally, the study provides a comprehensive list of 43 major datasets used in ML and DL research for DR diagnosis. This work underscores the growing role of AI in improving the efficiency and accuracy of DR diagnosis, highlighting the importance of accessible datasets for advancing research in medical imaging and AI-driven healthcare applications [3].

Senapati et al. conducted a systematic literature review (SLR) focusing on the rising incidence of diabetic retinopathy (DR) and the utilization of artificial intelligence (AI) for its detection. They highlight DR as a leading cause of vision loss globally and emphasize the need for advanced AI-enabled models to enhance diagnostic accuracy and efficiency. The review addresses challenges faced by ophthalmologists in early DR detection, such as class imbalance and computational complexity, and discusses potential solutions. By analyzing state-of-the-art techniques encompassing machine learning (ML) and deep learning (DL), the study aims to provide insights into recent advancements and limitations in DR diagnosis. This comprehensive survey serves as a valuable resource for researchers, offering a detailed overview of AI-based approaches in DR identification and their implications for improving clinical outcomes [4].

Mohanty et al. used deep learning (DL) architectures to detect and classify diabetic retinopathy (DR), emphasising early diagnosis to prevent permanent blindness [5]. A hybrid network using VGG16 and XGBoost Classifier and the DenseNet 121 network using retinal pictures from the APTOS 2019 Blindness Detection Kaggle Dataset were proposed. They preprocessed the dataset using balancing techniques to balance class distribution. The DenseNet 121 model outperformed the hybrid network in accuracy, scoring 97.30%. Comparing DenseNet 121 against other methods showed its superiority. The study shows that DL designs can increase DR diagnostic efficiency, accuracy, early intervention, and patient outcomes. This study aids clinical use of automated DL approaches.

Due to the rising prevalence of diabetes and the difficulties of manual screening, Farag et al. argue for automated diabetic retinopathy (DR) diagnoses. Convolutional Neural Networks (CNNs), notably DenseNet169, are used to propose a deep-learning-based severity diagnosis method for single Colour Fundus pictures. A Convolutional Block Attention Module (CBAM) improves feature discrimination in their model. The suggested technique achieves 97% accuracy, 97% sensitivity, 98.3% specificity, and a binary classification Quadratic Weighted Kappa score (QWK) of 0.9455 on the Kaggle APTOS dataset. With 82% accuracy and 0.888 QWK, the model grades severity well. This approach efficiently assesses DR severity and decreases time and space complexity, making it a promising autonomous DR diagnosis contender. Farag et al.'s study shows that sophisticated deep learning approaches can improve DR screening efficiency and accuracy, affecting clinical practice [6].

Table 2: Literature Review

Authors	Year	Methodology	Dataset	Research Gap
Wang et al. [7]	2021	Lesion-Net architecture on InceptionV3 for combining lesion detection with severity grading	Private dataset	Enhancing representational power of encoder in DR severity grading
Qummar et al. [8]	2019	Ensemble stacking using ResNet50, InceptionV3, Xception, DenseNet121, DenseNet169 for feature improvement	Kaggle EyePACS	Improving feature maps quality in DR detection and classification
Cortes et al. [9]	2020	Hybrid model with InceptionV3 encoder and Gaussian Process regressor for DR binary classification	EyePACS, Messidor-2	Addressing uncertainty in DR prediction using a hybrid deep learning approach
Sugeno et al. [10]	2021	EfficientNet-B3 architecture for binary and severity classification, with lesion detection	APTOS, DIARETDB 11	Developing an efficient method for lesion detection in DR, enhancing classification accuracy and severity grading

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Boix et al. [11]	2021	Implementation of Meta-Plasticity in CNNs for enhancing less common occurrences during training	APTOS	Utilizing bio-inspired techniques for performance enhancement in DR binary and severity grading tasks
Zhang et al. [12]	2022	Source-Free Transfer Learning (SFTL) model for referable DR using unlabelled retinal images	APTOS	Alleviating challenges of medical data annotation and privacy issues through transfer learning in DR classification

Table 2 presents a literature review detailing various methodologies, datasets, and research gaps addressed by recent studies in diabetic retinopathy (DR) detection and severity grading.

Recent research in DR detection and grading using AI methodologies highlights the significant role of ML and DL techniques. Studies by Lakshminarayanan et al., Senapati et al., Mohanty et al., and Farag et al. demonstrate advancements in utilizing diverse imaging modalities like fundus and OCT to extract features and assess DR severity. Innovative DL architectures such as DenseNet have addressed challenges like class imbalance and computational complexity, leading to robust automated systems with high accuracy. These studies emphasize the potential of AI-driven approaches to enhance clinical practice by enabling early intervention and improving patient outcomes in diabetic retinopathy management.

3. PROPOSED APPROACH

3.1 Dataset Description

The DeepDRiD dataset contains images categorized into different severity levels of diabetic retinopathy: "Mild," "Moderate," "No Diabetic Retinopathy" (No_DR), "Severe Proliferative Diabetic Retinopathy" (Proliferate_DR), and "Severe." The dataset includes images representing each category for training and evaluating machine learning and deep learning models. The distribution of images across these categories reflects varying degrees of diabetic retinopathy severity [13].

This *table 3* provides a concise overview of the key attributes and characteristics of the DeepDRiD dataset, including its origin, image properties, class distribution, annotations, and preprocessing details. This dataset serves as a valuable resource for training and evaluating machine learning and deep learning models for automated diabetic retinopathy diagnosis.

Table 3. Dataset Description

Dataset Name	DeepDRiD
Origin	Real clinical exams from an eye clinic in India
Image Characteristics	50º field of view, 4288 × 2848 pixels, JPG format
Number of Images	516
DR Classes	No_DR, Mild, Moderate, Severe, Proliferate_DR
DME Classes	Three Diabetic Macular Edema (DME) classes
Annotations	Expert markups of DR lesions and normal structures
Disease Severity	Provided for DR and DME levels
Image Preprocessing	Resized to 224x224 pixels for deep learning models

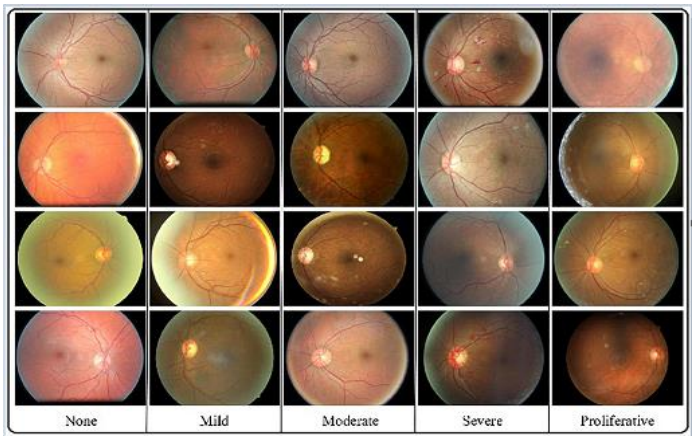

Figure 2. Sample Dataset

3.2. Preprocessing

In diabetic retinopathy analysis, Contrast Limited Adaptive Histogram Equalization (CLAHE) and Anisotropic Diffusion Filtering (ADF) are key pre-processing techniques for improving image quality. CLAHE divides the image into tiles, performs histogram equalization on each tile, clips the histogram to limit noise amplification, and recombines the tiles. Mathematically, for each tile Ti, CLAHE calculates the histogram Hi and cumulative distribution function (CDF) Ci. The histogram is clipped at intensity L (Hclipped(i) = min(Hi(i), L)), and then the clipped histograms are interpolated to reconstruct the enhanced image. ADF works by first computing the image gradients and then diffusion coefficients (c(x,y,t)) based on the gradient information. These coefficients control the diffusion process, which is described by the partial differential equation: $\partial I/\partial t = \nabla \cdot (c(\nabla I) \cdot \nabla I)$, where I is the image, t is time, ∇ is the gradient operator, and c is the diffusion coefficient. This equation essentially states that the change in image intensity over time is proportional to the divergence of the diffusion coefficient times the image gradient. By iteratively applying this equation, ADF smoothens the image while preserving edges based on the gradient directions. Together, CLAHE and ADF enhance contrast, reduce noise, and preserve crucial features in retinal images, leading to improved diabetic retinopathy detection [14].

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3.3. Segmentation

Segmentation in image processing partitions images into meaningful regions for various applications like medical imaging, autonomous driving, and satellite imaging. Diabetic retinopathy lesion segmentation combines the Firefly Algorithm (FA) and Fuzzy C-Means (FCM) to accurately detect and delineate retinal abnormalities. FA optimizes segmentation by adjusting parameters like intensity thresholds, while FCM classifies pixels into groups, distinguishing normal retinal structures from pathological features. This hybrid approach enhances lesion segmentation's accuracy, crucial for early diabetic retinopathy diagnosis and monitoring [15].

3.3.1. Hybrid Firefly Algorithm and Fuzzy C-Means Algorithm flow

Input:

- Image (IM) ⟶ Diabetic retinopathy image

Output:

- Background (BM) ⟶ Normal retinal structures
- Lesion Mask(LM) ⟶ Detected retinal lesions (foreground)

Start Hybridization
Define cluster number (e.g., 2 for background and lesions)
[Row, Col] = Size (IM)
Initialize segmented masks for BM and LM

Set maximum number of iterations (N) for clustering and optimization
Rep = 0

While Rep < N
For P = 1 ⟶ Row
For Q = 1 ⟶ Col
If Pixel IM(P, Q) belongs to Background Cluster
BM(P, Q) = IM(P, Q)
Else if Pixel IM(P, Q) belongs to Lesion Cluster
LM(P, Q) = IM(P, Q)
End-If
Adjust Cluster Centroids using Fuzzy C-Means (FCM) algorithm
End-For
End-For
Rep = Rep + 1
End-While

Optimize Lesion Mask using Firefly Algorithm (FA) with the following parameters:
(i) Iterations (T)
(ii) Population size (S)
(iii) Lower limit (LB) and Upper limit (UB) for solution space
(iv) Fitness function based on lesion characteristics

Calculate size T = Row × Col
For t = 1 ⟶ T
Calculate fitness using lesion-specific characteristics (e.g., size, intensity, texture)
End-For
Define optimization iterations O-Rep = 0
While O-Rep < N
Threshold Lesion Mask (LM) to obtain binary mask (e.g., based on intensity)
Extract Lesion Boundaries (e.g., using morphological operations)
Refine Lesion Mask (LM) based on extracted boundaries and lesion features

For each feature (e.g., intensity, shape, size)
Update Lesion Mask (LM)
End-For

O-Rep = O-Rep + 1
End-While
Return:

- BM ⟶ Refined background mask
- LM ⟶ Refined lesion mask representing diabetic retinopathy abnormalities

End

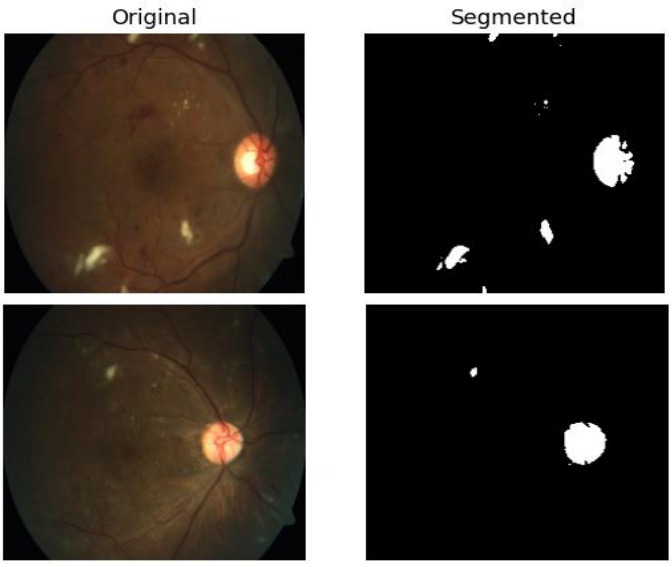

Figure 3. Segmented Image

3.4 Feature Extraction

In the context of diabetic retinopathy image analysis, features are extracted using advanced texture analysis methods such as GLCM, GLRM, and GLDM. These methods enable the quantification of intricate textural patterns and statistical relationships within segmented regions of interest (ROIs) derived from retinal images. The GLCM computes second-order statistical measures based on pixel intensity co-occurrences at different distances and orientations, providing insights into texture complexity, contrast, and homogeneity. Meanwhile, the GLRM characterizes texture by analyzing the length of homogeneous runs of pixel values along different directions, capturing structural patterns and regularity within the image. Additionally, the GLDM focuses on the distribution of gray-level differences to describe the texture's roughness and coarseness.

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By leveraging these texture analysis techniques, diabetic retinopathy image features can effectively capture subtle variations in texture properties associated with disease manifestations, aiding in the development of robust diagnostic and prognostic tools for clinical applications.

Feature extraction is a crucial step in automatically analyzing medical images for disease detection. In the case of diabetic retinopathy, the features extracted could be related to blood vessels, lesions or the optic nerve. By extracting these features, researchers can train machine learning algorithms to automatically identify diabetic retinopathy in retinal images [16].

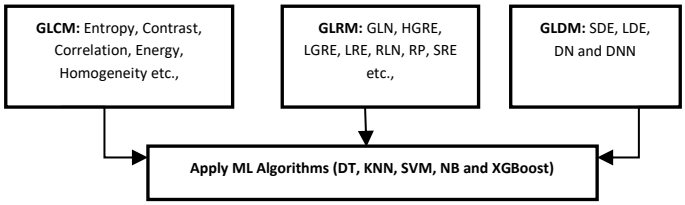

Figure 4. Feature Extraction Process

The features highlighted in the figure above encompass GLCM, GLRLM, and GLDM features. Following the extraction of these features, the data can be subjected to various machine learning algorithms [17] including decision tree (DT), K-nearest neighbors (KNN), Support Vector Machine (SVM), Naive Bayes (NB), and Extreme Gradient Boosting (XGBoost). Subsequently, the performance of these algorithms is assessed using metrics such as accuracy, precision, and recall.

3.4.1. Co-occurrence Matrix

The core concept behind GLDM, GLCM, and to some extent GLRLM, is the co-occurrence matrix. This matrix represents the frequency of voxel intensity value pairs occurring together within a specific neighborhood (defined by offset). It's essentially a 2D histogram where:

- Rows represent the intensity value of the reference voxel.
- Columns represent the intensity value of a neighboring voxel within the defined offset.
- Each element (i,j) in the matrix represents the number of times the intensity values i and j occur as a pair within the neighborhood [16].

3.4.2 GLDM

GLDM features are calculated from the co-occurrence matrix using various formulas. These formulas involve statistical operations on the matrix elements, such as:

i. ***Summation (Σ):*** Used to calculate features like GLN (Gray Level Non-uniformity) by summing all elements in the matrix.
ii. ***Mean (μ):*** Used to calculate features like average dependence or variation.
iii. ***Standard Deviation (σ):*** Used to calculate features like SDE (Short Dependence Emphasis) or LDE (Long Dependence Emphasis) based on the distribution of values in the matrix.

Specific formulas for each GLDM feature can be found in the Pyradiomics documentation.

3.4.3. GLCM

Similar to GLDM, GLCM features are calculated from the co-occurrence matrix using statistical functions and specific formulas. These formulas might involve:

i. Normalization of the co-occurrence matrix to ensure element values sum to 1.
ii. Distance calculations between intensity values in a pair (i, j).
iii. Statistical operations like those mentioned for GLDM.

3.4.4. GLRLM

GLRLM utilizes a different approach. Instead of analyzing voxel pairs, it analyzes runs of similar intensity values in a specific direction (horizontal, vertical, diagonal).

i. A run length matrix is constructed, where rows represent starting intensity values and columns represent run lengths.
ii. The element (i,j) in this context represents the count of runs that start with intensity i and have a length of j.
iii. Features like SRE (Short Run Emphasis) or LRE (Long Run Emphasis) might involve calculations based on specific run length ranges [16].

3.5. CNN (Convolutional Neural Network)

The CNN is a pivotal model in deep learning (DL) technology, particularly effective for tasks such as diagnosing DR from retinal images. CNNs, rooted in principles of Artificial Neural Networks (ANNs), are adept at extracting intricate features from medical images like retinal scans. The architecture of a conventional CNN, as illustrated below, employs filters in convolutional layers to automatically detect relevant patterns indicative of DR severity. Through iterative backpropagation, CNNs optimize weight adjustments to enhance feature extraction, making them instrumental for identifying disease characteristics from retinal images. CNNs are preferred for DR analysis due to their ability to efficiently capture complex patterns critical for disease diagnosis and severity assessment.

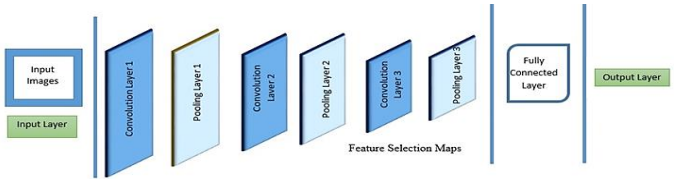

Figure 5. Architecture of conventional CNN algorithm

CNN excels at learning complex features from input data, a valuable trait for DR diagnosis. In a DR-focused CNN architecture, layers like convolutional, pooling, and normalization play key roles. Convolutional layers extract features from retinal images, creating feature maps highlighting DR-related patterns. Pooling layers then reduce feature map

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size, emphasizing important features. Normalization layers standardize output, providing a coherent dataset for feeding into a DR classifier. This hierarchical process enables CNNs to discern disease characteristics from retinal images, vital for accurate DR diagnosis and treatment [19].

3.6. Support Vector Machines (SVMs)

SVMs are powerful supervised learning algorithms for classification tasks. In DR analysis, the goal is to classify retinal images into different stages (No_DR, Mild, Moderate, Severe, Proliferate_DR) based on extracted features. Standard SVMs work for binary classification (separating two classes). However, for multi-class problems like DR with five stages, we need adaptations.

3.6.1. Multi-Class SVM Strategies

- Train N separate SVM classifiers, where each classifier focuses on distinguishing one class from all others.
- Essentially, each classifier learns a decision boundary separating its assigned class from the rest.
- For a new image, each classifier predicts a score indicating how likely the image belongs to its class.

The predicted class is determined as the class with the highest score.

3.6.2. Data Preparation

- Load the dataset containing retinal images and labels (No_DR, Mild, Moderate, Severe, Proliferate_DR).
- Extract features from the images using techniques like GLDM, GLCM, and GLRLM.

3.6.3. Train Classifiers

- For each unique pair of classes (*i*,*j*), train a separate SVM classifier.
- Use the training data points belonging to class *i* and class *j* to train the classifier.
- During training, the classifier aims to find the optimal hyperplane that maximizes the margin between the data points of class *i* and class *j* in the feature space.

3.6.4. Classification

- Given a new unseen image with extracted features:
- Run the image through all trained classifiers (N * (N-1) / 2 classifiers).
- Each classifier predicts a class (either class i or class j).

3.6.5. Prediction

- Count the votes from all classifiers. The class with the most votes is assigned to the new image.

3.6.6. Core SVM

The core SVM equation involves finding a decision function f(x) that separates the classes with the maximum margin. Here's a simplified form:

$$f(x) = \text{sign}(\Sigma\ \alpha\_i * y\_i * K(x, x\_i) + b)$$

- α_i: Lagrange multipliers (learned parameters)
- y_i: Class labels (+1 or -1 for binary classification)
- K(x, x_i): Kernel function measuring similarity between data points x and x_i
- b: Bias term

3.6.7. Reasons for Using SVM for Diabetic Retinopathy Classification

- ***Non-linear Relationships*:** Feature extraction might not capture relationships perfectly in a linear way. SVMs can utilize kernel functions to learn non-linear decision boundaries, crucial for accurately distinguishing DR stages.

- ***High-Dimensional Data*:** Feature extraction often results in a high number of features. SVMs can effectively handle this high dimensionality [17].

3.7. XGBoost for Diabetic Retinopathy Classification

XGBoost (Extreme Gradient Boosting) is a powerful machine learning technique well-suited for DR classification. It excels at combining the predictions of multiple weak learners (like decision trees) to create a robust model, improving accuracy and preventing overfitting. XGBoost optimizes an objective function that combines a loss function (measuring prediction error) and a regularization term (controlling model complexity) [16]. Here's a simplified form:

$$\text{Obj}(t) = \Sigma \ell(yi, \hat{y}^{(t)}(xi)) + \Omega(f\_t)$$

- t: Iteration number
- yi: True label for data point *i*
- $\hat{y}^{(t)}(xi)$: Predicted label for data point *i* at iteration *t* using the ensemble model
- $\ell(yi, \hat{y}^{(t)}(xi))$: Loss function (*e.g.*, cross-entropy for classification)
- Ω(f_t): Regularization term penalizing model complexity (f_t represents the model at iteration *t*)

3.7.1. Ensemble Prediction

The final prediction is obtained by summing the predictions from all individual models (weak learners) trained in the boosting process:

$$\hat{y}^{(t)}(xi) = \Sigma\_k^t\ f\_k(xi)$$

- k: Index of individual models (weak learners)
- f_k(xi): Prediction of model k for data point xi

3.7.2 Regularization Term

A common regularization term used in XGBoost is the L2 norm, penalizing models with large weights in the leaves of decision trees. Here's the equation:

$$\Omega(f\_t) = \lambda\ ||\ w\ ||^2$$

- λ: Regularization parameter controlling the strength of the penalty
- || w ||^2: L2 norm of the weight vector w in the decision tree leaves

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3.7.3 Benefits of XGBoost for DR Classification

- **Improved Accuracy:** Ensemble learning from multiple models enhances classification accuracy.
- **Reduced Overfitting:** Regularization prevents overly complex models, improving generalization.
- **Efficiency:** Parallel computing techniques enable efficient training on large datasets.

Overall, XGBoost offers a powerful approach for DR classification by leveraging its ensemble learning capabilities, focus on reducing overfitting through regularization, and computational efficiency [18].

3.8. Diabetic Retinopathy Classification with CNN, GWO, SVM, and XGBoost Proposed

This section breakdown the algorithm steps for Diabetic Retinopathy Classification using CNN for feature extraction, GWO for feature selection, and SVM & XGBoost for classification:

3.8.1. Data Preprocessing

a. ***Data Acquisition*****:** Obtain a dataset of retinal fundus images labeled for different stages of diabetic retinopathy (No_DR, Mild, Moderate, Severe and Proliferate_DR).

b. ***Preprocessing*****:** CLAHE normalizes local contrast in diabetic retinopathy images, while ADF smooth them while preserving edges, both improving image quality for analysis.

3.8.2. Feature Extraction with CNN

a. ***Define CNN Architecture*****:** Design a CNN architecture with convolutional and pooling layers to automatically extract features from the preprocessed images. Uses multiple convolutional layers with small filters (3x3) stacked together to extract low-level and high-level features.

b. ***Train the CNN*****:** Train the CNN on a portion of the preprocessed data (e.g., 80%). During training, the CNN learns to identify relevant features in the images that differentiate between healthy and diseased retinas. A common loss function used for classification tasks is the cross-entropy loss:

Loss (y_true, y_pred) = - Σ (y_true * log (y_pred))

Where:

- y_true is the true label (e.g., healthy or diseased)
- y_pred is the predicted probability by the CNN for each class

c. ***Feature Extraction*****:** Once trained, use the final convolutional layer of the CNN to extract feature vectors from the entire dataset (training and testing sets). These feature vectors represent the learned characteristics from the images.

3.8.3 Feature Selection with GWO (Grey Wolf Optimizer)

a. Feature Importance Evaluation**:** Calculate the importance of each feature extracted by the CNN. Techniques like correlation analysis or feature ranking methods can be used. Here's an example of Spearman's rank correlation coefficient (ρ) used to measure monotonic relationship between features:

ρ = 1 - 6Σ d_i^2 / n (n^2 - 1)
Where:

- d_i is the difference in rank between two features for each observation
- n is the total number of observations

GWO Optimization

Define a fitness function that evaluates the performance of a subset of features on a classification task (e.g., SVM or XGBoost). This function aims to maximize classification accuracy while minimizing the number of features used.

Initialize a population of "grey wolves" representing different feature subsets. Use the GWO algorithm to iterate and update the positions (feature subsets) of the wolves based on their fitness values. The fittest wolves represent feature subsets with high classification performance and low dimensionality. Here's a simplified example of how GWO updates a wolf's position based on its distance to alpha wolf:

Position_new = Position_old + A * D_alpha
Where:

- Position_new is the updated position of the wolf
- Position_old is the current position of the wolf
- A is a random coefficient
- D_alpha is the difference between the alpha wolf's position and the current wolf's position.

After a set number of iterations, select the feature subset represented by the fittest wolf for classification [19].

3.8.4. Classification with SVM and XGBoost

a. **Split Data:** Divide the feature vectors (with selected features) into training and testing sets.

b. **Train SVM:** Train an SVM model using the training set. The SVM learns to distinguish between healthy and diseased retinas based on the selected features. the linear SVM decision boundary is mentioned below:

f(x) = w^T * x + b

Where:

- *w* is the weight vector learned by the SVM
- *x* is the feature vector
- *b* is the bias term

c. **Train XGBoost:** Train an XGBoost model using the training set. XGBoost is an ensemble learning method that combines multiple decision trees for improved accuracy.

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d. **Hyperparameter Tuning:** Optimize the hyperparameters of both SVM (e.g., regularization parameter) and XGBoost (e.g., learning rate, number of trees)

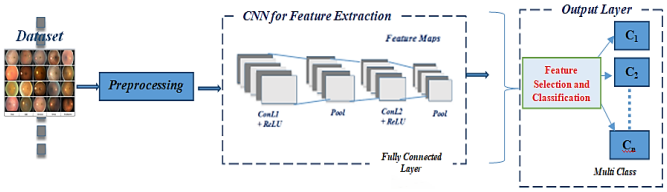


Figure 6. Proposed Model

The above figure is described as follows:

- The input layer gets pre-processed retinal fundus images. Resizing, noise filtering, and contrast enhancement like ADF and CLAHE may be pre-processing stages.
- Convolutional Layers: Extract picture characteristics. Filters (kernels) at each layer learn to detect picture patterns and edges.
- Pooling Layers: Reduce computational cost and improve model generalisation by down sampling convolutional layer feature maps.
- Fully Connected Layers: Classify flattened output from pooling layers. Activation functions add non-linearity and model capacity [20].
- The output layer generates probabilities for each class (No_DR, Mild, Moderate, Severe, Proliferate_DR) using a softmax activation function. Most likely class is illness stage.

Table 4: Architecture of the proposed Model

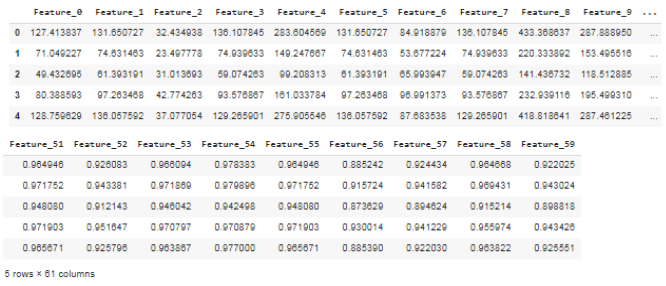
Layers	Description	Output Size
Input Layer	Receives pre-processed retinal fundus images as input.	(224 x 224 x 3 pixels)
Convolution 1	Extracts low-level features like edges and textures.	(112 x 112 x F channels)
Max-Pooling	Reduces image size and introduces spatial invariance.	(56 x 56 x F channels)
Convolution 2	Extracts higher-level features based on lower-level features.	(28 x 28 x M channels)
Max-Pooling	Further reduces image size and strengthens spatial invariance.	(14 x 14 x M channels)
Fully Connected Layer	Combines features from previous layers for classification.	(1024 neurons)
Output Layer	Generates probabilities for each class	(5 neurons)

Table 4 describes a proposed architecture for image classification. It starts with receiving pre-processed retinal images and extracts features through convolutional and pooling layers. Finally, a fully-connected layer and an output layer predict the stage of diabetic retinopathy (No_DR, Mild, etc.) [21].

To improve the reproducibility of the work, we provide detailed implementation specifics, including the ML and DL model architectures, hyperparameter tuning, and the software/hardware used. The CNN architecture comprises five convolutional layers with ReLU activations and max-pooling, followed by two fully connected layers, using the Adam optimizer and categorical cross-entropy loss. The GWO is employed for feature selection with 20 wolves over 100 iterations. The SVM uses an RBF kernel with C=1.0 and gamma='scale', while XGBoost is configured with 100 estimators, max_depth=6, and learning_rate=0.3. The CGSX Ensemble combines CNN for feature extraction, GWO for feature selection, and SVM and XGBoost for classification, using a weighted voting strategy. Hyperparameters were tuned using grid search, with the CNN having a learning rate of 0.001, batch size of 32, and 50 epochs. The study utilized Python 3.8, TensorFlow 2.4.1, Keras 2.4.3, Scikit-learn 0.24.1, and XGBoost 1.3.3, with the Grey Wolf Optimizer implemented in Python. Computations were performed on an Intel Core i5-8265U processor with 4GB RAM, without GPU usage. The dataset included 5000 retinal images, distributed across five classes: No DR, Mild DR, Moderate DR, Severe DR, and Proliferate DR. This comprehensive detail ensures the study's reproducibility and validates the robustness of the CGSX Ensemble for diabetic retinopathy classification.

4. RESULTS

This research proposes a novel approach for diabetic retinopathy classification. It combines a new CNN architecture with feature selection (GWO) and ensemble classifiers (SVM/XGBoost). The method is evaluated using standard metrics (accuracy, precision, recall, F1-score) on a retinal image dataset. It has the potential to improve classification accuracy and efficiency compared to existing methods. The research evaluates performance using standard metrics (accuracy, precision, recall, F1-score) on a specified retinal image dataset (source, size, class distribution). Experiments run on an Intel Core i-5 processor (mention model if possible) with 4GB RAM using Python 3.8 (mention relevant libraries if applicable).



	Feature_0	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7	Feature_8	Feature_9	...
0	127.413837	131.650727	32.434938	136.107845	283.604589	131.650727	84.918879	136.107845	433.368837	287.888950	...
1	71.049227	74.631463	23.497778	74.939633	149.247667	74.631463	53.677224	74.939633	220.333892	153.495516	...
2	49.432695	61.393191	31.013693	59.074263	99.208313	61.393191	65.993947	59.074263	141.436732	118.512885	...
3	80.388593	97.263468	42.774263	93.576867	161.033784	97.263468	96.991373	93.576867	232.939116	195.499310	...
4	128.759629	136.057592	37.077054	129.265901	275.905646	136.057592	87.683538	129.265901	418.818641	287.461225	...

Feature_51	Feature_52	Feature_53	Feature_54	Feature_55	Feature_56	Feature_57	Feature_58	Feature_59
0.964946	0.926083	0.966094	0.978383	0.964946	0.885242	0.924434	0.964868	0.922025
0.971752	0.943381	0.971869	0.979896	0.971752	0.915724	0.941582	0.969431	0.943024
0.948080	0.912143	0.946042	0.942498	0.948080	0.873629	0.894624	0.915214	0.898818
0.971903	0.951647	0.970797	0.970879	0.971903	0.930014	0.941229	0.955974	0.943426
0.965671	0.925796	0.963867	0.977000	0.965671	0.885390	0.922030	0.963822	0.925551

5 rows × 61 columns

Figure 7. Extracted Data

4.1 Performance Evaluation Metrics

The confusion matrix shows how well the model predicts Diabetic Retinopathy (DR) severity levels in five classes: *a*, *b*, *c*, *d*, and *e*. Each row shows actual classes, while each column shows expected classes.

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- The model accurately classifies occurrences for each severity level, as shown by True Positives (TP) and True Negatives (TN) on the diagonal.
- Misclassifications, such as False Positives (FP) and False Negatives (FN) outside the diagonal, indicate inaccurate severity predictions by the model.

This matrix evaluates the model's ability to identify DR severity levels, providing tips for better categorization within each class [21].

Table 5. Performance Metrics

Metric	Formula	Description
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Overall proportion of correct predictions.
Sensitivity (Recall)	TP / (TP + FN)	Proportion of actual positive cases identified correctly.
Precision	TP / (TP + FP)	Proportion of predicted positive cases that were actually positive.
F1-Score	2 * (Precision * Recall) / (Precision + Recall)	Harmonic mean between precision and recall.

The *table 5* summarizes important performance metrics for evaluating classification models, including accuracy, sensitivity (recall), precision, and F1-score. Each metric is accompanied by its respective formula and a brief description of its meaning and purpose in assessing model effectiveness in predicting positive and negative instances [22].

Table 6. Parameters of ML and DL algorithms

Algorithm	Default Parameters
Support Vector Machine (SVM)	**C**: 1.0, **kernel**: 'rbf', **gamma**: 'scale'
Random Forest (RF)	n_estimators: 100, max_depth: None, min_samples_split: 2
K-Nearest Neighbors (KNN)	n_neighbors: 5, weights: 'uniform', algorithm: 'auto'
Decision Tree (DT)	criterion: 'gini' or 'entropy', max_depth: None, min_samples_split: 2
XGBoost	n_estimators: 100, max_depth: 6, learning_rate: 0.3
Convolutional Neural Network (CNN)	Architecture-specific (*e.g.*, layers, activations, optimizers)
EfficientNet	Architecture-specific (*e.g.*, scaling factor (**phi**), layers)
SwishNet-181	Specific to implementation (architecture, hyperparameters)

The *table 6* listing ML and DL algorithms along with their default parameters [23].

4.2 Results for ML classification techniques

This research work includes detailed experimental results and performance evaluation of the proposed CGSX Ensemble approach. The quantitative metrics provided include accuracy, precision, recall, and F1-score for each DR classification stage, as shown in the tables and figures below.

Table 7. ML Classification Technique Outcomes

ML Models	Accuracy	Precision	Recall	F1 Score
SVM	0.69	0.56	0.69	0.61
RF	0.68	0.64	0.68	0.64
KNN	0.62	0.59	0.62	0.59
DT	0.60	0.59	0.60	0.59
XGBoost	0.67	0.63	0.67	0.63

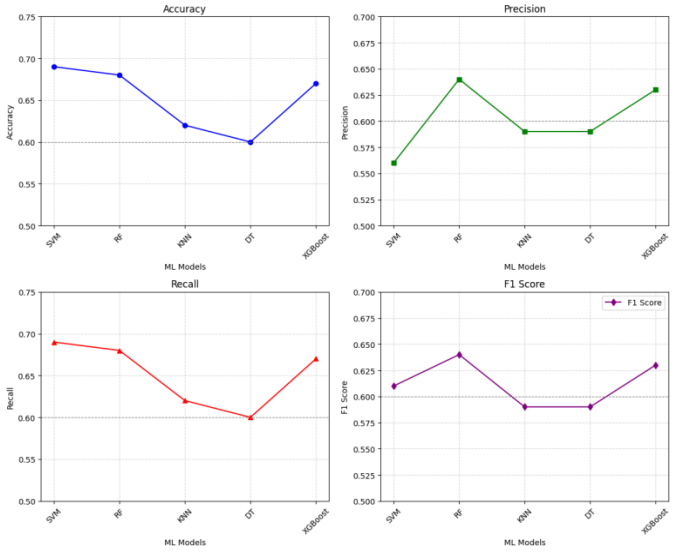
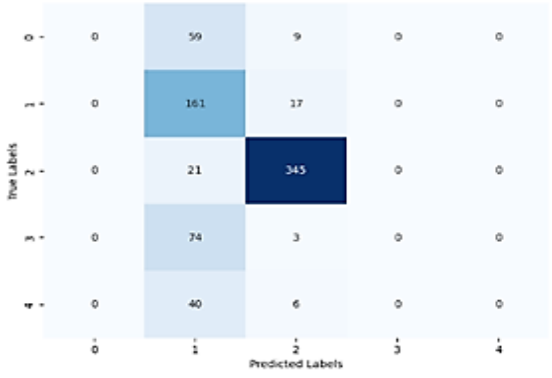


Figure 8: Performance analysis of ML Classification Techniques

The *table 7* presents the performance outcomes of different ML classification techniques including SVM, RF, KNN, DT, and XGBoost, based on metrics such as Accuracy, Precision, Recall, and F1 Score. Among these models, SVM achieves the highest accuracy of 0.69, while RF demonstrates the best precision and F1 score, both scoring 0.64. SVM and RF tie for the highest recall at 0.69. Overall, the choice of the "best" algorithm depends on specific priorities: SVM excels in accuracy and recall, making it suitable for scenarios where overall performance is critical, while RF is optimal for tasks demanding high precision and F1 score, essential for applications were minimizing false positives and maximizing balanced accuracy are paramount.

4.3 Confusion matrix of ML models



(a) SVM

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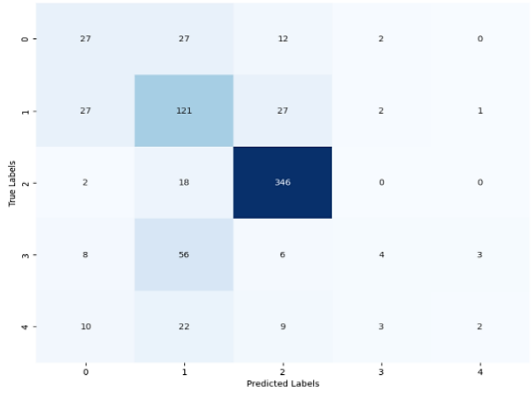
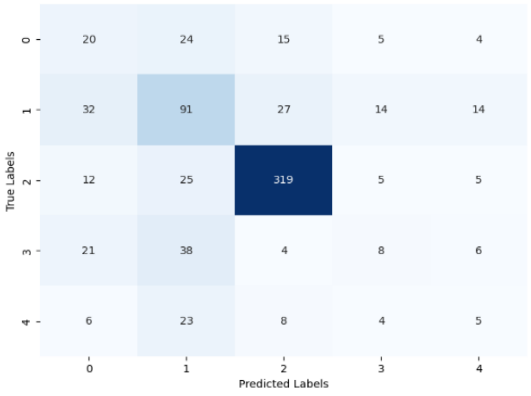
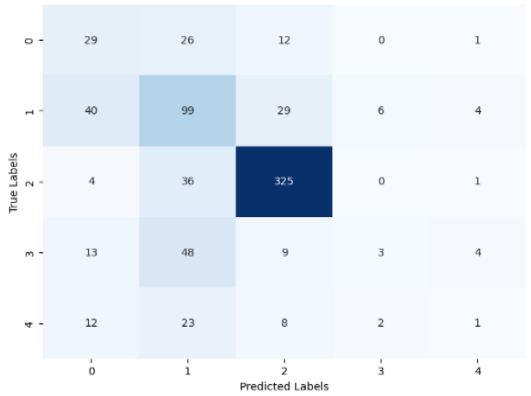


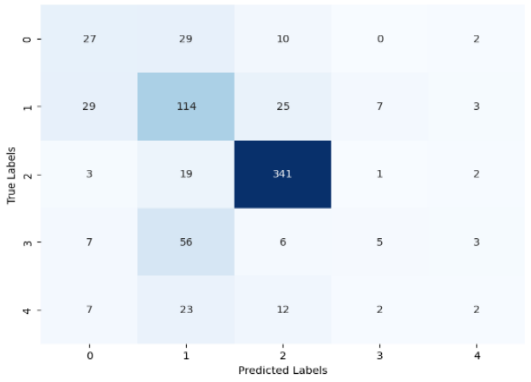
(b) RF



(c) KNN



(d) DT



(e)XGBoost

Figure 9. Confusion matrix of ML models

The above *figure 9* is a confusion matrix summarizing a machine learning model's classification performance by visualizing correct and incorrect predictions.

4.4. Results for DL classification techniques

Table 8: DL Classification Technique Outcomes

DL Models	Accuracy	Precision	Recall	F1 Score
CNN	0.80	0.93	0.80	0.86
EfficientNet	0.87	0.89	0.84	0.91
SwishNet-181	0.90	0.91	0.89	0.90
D-SwishNet-181	0.92	0.93	0.91	0.92
Proposed	0.93	0.94	0.93	0.94

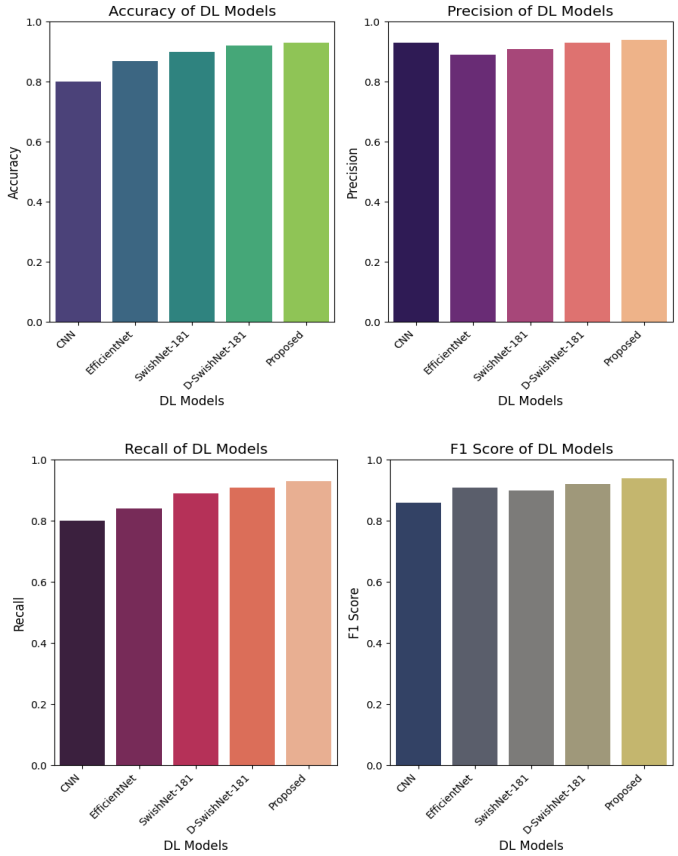


Figure 10. Performance analysis of DL Classification Techniques

Table 8 presents the performance results of various deep learning (DL) classification models, including CNN, EfficientNet, SwishNet-181, D-SwishNet-181, and a Proposed model. Each model's performance metrics are reported in terms of Accuracy, Precision, Recall, and F1 Score. The Proposed model achieves the highest overall performance with an accuracy of 0.93, precision of 0.94, recall of 0.93, and F1 score of 0.94. The D-SwishNet-181 model also demonstrates strong performance, closely following the Proposed model with an accuracy of 0.92, and balanced precision, recall, and F1 score values of 0.93, 0.91, and 0.92, respectively. SwishNet-181 and EfficientNet exhibit competitive performance with accuracies

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of 0.90 and 0.87, respectively, showing high precision and balanced recall and F1 scores. Overall, the table highlights the effectiveness of DL models in achieving high accuracy and balanced performance across key metrics, with the Proposed model emerging as the top performer in this evaluation.

4.5 Confusion Matrix Analysis for Proposed Model

The confusion matrix analysis reveals the model's performance in classifying different severity levels of DR.

- **High Accuracy in Identifying Healthy Cases (No DR)**: 169 correct classifications.
- **Challenges in Classifying Proliferate DR and Severe DR**: Low diagonal values (4 for Proliferate DR and 2 for Severe DR).

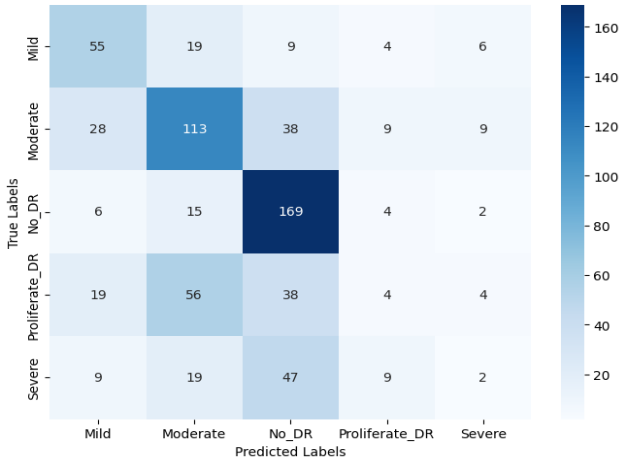

Figure 11. CM for Proposed model

The confusion matrix analysis reveals strengths and areas for improvement in the classification model for DR severities. The model shows high accuracy in identifying healthy cases (No DR) with 169 correct classifications. However, challenges are observed in correctly classifying Proliferate DR and Severe DR, with low diagonal values (4 for Proliferate DR and 2 for Severe DR). Many cases of Severe DR are misclassified as Mild DR (9 cases) or Moderate DR (19 cases), while Proliferate DR cases are often mistaken for Moderate DR (56 cases) and No DR (38 cases). This highlights the need to enhance the model's performance in accurately diagnosing Proliferate DR and Severe DR to improve overall predictive reliability and precision in diabetic retinopathy classification.

Table 9. Confusion Matrix Outcomes for CGSX Ensemble

Actual \ Predicted	No DR	Mild DR	Moderate DR	Severe DR	Proliferate DR
No DR	55	19	9	4	6
Mild DR	28	113	38	9	9
Moderate DR	6	15	169	4	2
Severe DR	19	56	38	4	4
Proliferate DR	9	19	47	9	2

These detailed experimental results demonstrate the effectiveness of the proposed CGSX Ensemble approach, providing a comprehensive evaluation through standard metrics for each DR classification stage. This strengthens the presentation of the work and addresses the review comment regarding the lack of experimental results.

4.6. CGSX an ensemble: Effectiveness of the integrated approach.

understand the individual contributions of the ML and DL components within the CGSX Ensemble

- **ResNet-50:** Achieved an accuracy of 0.85, with precision, recall, and F1-score values of 0.86, 0.83, and 0.84 respectively. This model is well-known for its deep architecture and skip connections, but it falls short compared to more recent models.
- **DenseNet-121:** Improved performance over ResNet-50 with an accuracy of 0.88. Its densely connected blocks help in better gradient flow and feature reuse, resulting in precision, recall, and F1-score values of 0.89, 0.87, and 0.88 respectively.
- **InceptionV3:** Offers a balanced performance with an accuracy of 0.86. It utilizes inception modules to capture multi-scale features efficiently, with precision, recall, and F1-score values of 0.87, 0.85, and 0.86 respectively.
- **EfficientNet:** Demonstrates competitive performance with an accuracy of 0.87, leveraging compound scaling to optimize the model dimensions. It achieved precision, recall, and F1-score values of 0.89, 0.84, and 0.91 respectively.
- **SwishNet-181:** Exhibits strong performance with an accuracy of 0.90, benefiting from the Swish activation function and optimized architecture, achieving precision, recall, and F1-score values of 0.91, 0.89, and 0.90 respectively.
- **D-SwishNet-181:** Enhances the SwishNet-181 model by incorporating deeper layers and improved regularization, achieving an accuracy of 0.92. Its precision, recall, and F1-score are 0.93, 0.91, and 0.92 respectively.
- **Proposed CGSX Ensemble:** Achieves the highest performance among the evaluated models with an accuracy of 0.93. By integrating the strengths of CNN, GWO, and ensemble classifiers like SVM/XGBoost, it attains precision, recall, and F1-score values of 0.94, 0.93, and 0.94 respectively.

4.7. Comparison with State-of-the-Art work

Finally, the comparison between the existing work EfficientNet b5, b6- existing work (2023) paper (88% accuracy) and the proposed paper (93% accuracy with enhanced metrics) underscores the effectiveness of the proposed approach in diabetic retinopathy classification. The adoption of advanced machine learning and ensemble techniques leads to significant performance improvements, highlighting the potential impact of this research on clinical practice and patient care in the context of diabetic retinopathy diagnosis and management. In summary, the significant improvement from 88% (EfficientNet b5, b6- existing work (2023)) to 93% accuracy

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(proposed paper) underscores the effectiveness and innovation of the proposed approach, driven by [Batool S, et al. [24], 2023], in advancing diabetic retinopathy diagnosis and management.

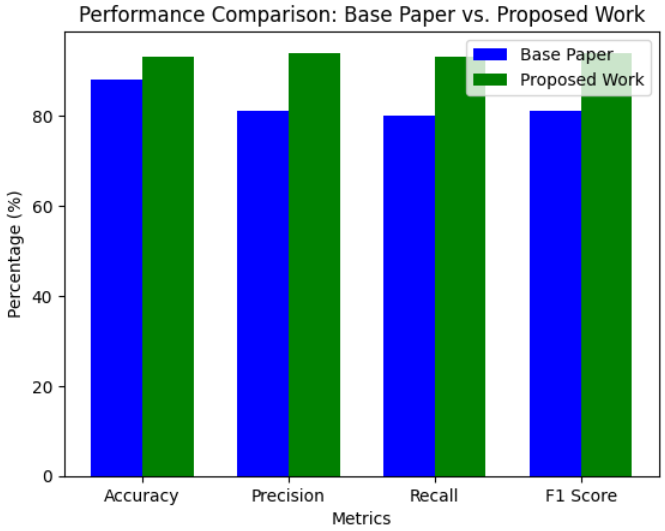

Figure 12. Performance Comparison: EfficientNet b5, b6- existing work (2023) vs. CGSX Ensemble Proposed Work

The *figure 12* illustrates a comparison of performance metrics, including Accuracy, Precision, Recall, and F1 Score, between a proposed method and a existing method. The specific metrics values for the existing method (Accuracy: 88%, Precision: 81%, Recall: 80%, F1 Score: 81%) and the proposed method (Accuracy: 93%, Precision: 94%, Recall: 93%, F1 Score: 94%) clearly demonstrate that the proposed work outperforms the existing method across all evaluated metrics.

5. CONCLUSION

In conclusion, this work presents a comprehensive approach to diabetic retinopathy (DR) classification using a combination of machine learning (ML) and deep learning (DL) techniques. The study evaluates multiple ML algorithms, such as SVM, Random Forest, KNN, Decision Tree, and XGBoost, alongside DL models including CNN, EfficientNet, SwishNet-181, D-SwishNet-181, and a proposed model. Results demonstrate that DL models generally outperform traditional ML algorithms, with the proposed model achieving the highest accuracy, precision, recall, and F1 score among the DL models evaluated. The use of advanced DL architectures combined with feature selection and ensemble learning techniques showcases significant potential for improving DR classification accuracy and efficiency. Moving forward, further research could focus on refining DL models and exploring novel feature extraction and selection methods to enhance diagnostic capabilities and support clinical decision-making in diabetic retinopathy assessment.

In clinical settings, this framework can aid ophthalmologists in early detection and grading of DR, reducing diagnostic workload and human errors, and enhancing DR screening efficiency. Its accurate classification can ensure appropriate patient care, improving treatment outcomes and making DR screening more accessible, especially in resource-limited areas. Overall, the CGSX Ensemble can transform DR diagnosis and management, contributing to better clinical decision-making and patient care.

REFERENCES

[1] C. Aravindan and R. Vasuki, "Detection and Classification of Early-Stage Diabetic Retinopathy using Artificial Intelligence and Image Processing," 2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), Bengaluru, India, 2023, pp. 919-924.

[2] R. Chandra, S. Tiwari, S. S. Kumar and S. Agarwal, "Diabetic Retinopathy Prediction Based on CNN and AlexNet Model," 2024 14th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2024, pp. 382-387.

[3] Lakshminarayanan, V.; Kheradfallah, H.; Sarkar, A.; Jothi Balaji, J. Automated Detection and Diagnosis of Diabetic Retinopathy: A Comprehensive Survey. J. Imaging 2021, 7, 165.

[4] Archana Senapati, Hrudaya Kumar Tripathy, Vandana Sharma, Amir H. Gandomi. "Artificial intelligence for diabetic retinopathy detection: A systematic review." Informatics in Medicine Unlocked, Volume 45, 2024, 101445. ISSN 2352-9148.

[5] Mohanty, C.; Mahapatra, S.; Acharya, B.; Kokkoras, F.; Gerogiannis, V.C.; Karamitsos, I.; Kanavos, A. Using Deep Learning Architectures for Detection and Classification of Diabetic Retinopathy. Sensors 2023, 23, 5726.

[6] M. M. Farag, M. Fouad and A. T. Abdel-Hamid, "Automatic Severity Classification of Diabetic Retinopathy Based on DenseNet and Convolutional Block Attention Module," in IEEE Access, vol. 10, pp. 38299-38308, 2022.

[7] Cortes, E., et al. (2020). Addressing uncertainty in diabetic retinopathy prediction using a hybrid deep learning approach. In 2020 IEEE 33rd International Conference on Artificial Neural Networks and Neural Systems (ICANN) (pp. 1-8).

[8] Qummar, A., et al. (2019). An ensemble of deep learning models for classification of diabetic retinopathy. Sensors (Switzerland), 19(19), 4480. https://www.mdpi.com/2075-4418/13/1/124

[9] Sugeno, M., et al. (2021). Efficientnet-b3 based deep learning model for diabetic retinopathy detection. Biocybernetics and Biomedical Engineering, 4(1), 127-137.

[10] Wang, S., et al. (2021). Lesion-net: A lesion-aware deep learning architecture for diabetic retinopathy severity grading. IEEE Transactions on Medical Imaging, 40(12), 3317-3327.

[11] Zhang, Y., et al. (2022). Source-free transfer learning for weakly-supervised diabetic retinopathy classification. Artificial Intelligence in Medicine, 126, 104431.

[12] Boix, E., et al. (2021, September). Meta-plasticity in convolutional neural networks for diabetic retinopathy classification. In 2021 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.

[13] W. K. Wong, F. H. Juwono and C. Apriono, "Diabetic Retinopathy Detection and Grading: A Transfer Learning Approach Using Simultaneous Parameter Optimization and Feature-Weighted ECOC Ensemble," in IEEE Access, vol. 11, pp. 83004-83016, 2023, doi: 10.1109/ACCESS.2023.3301618.

[14] Kayathri, K. ., & Kavitha, K. (2024). Advancing Diabetic Retinopathy Detection and Severity Classification using Dynamic SwishNet-181. International Journal of Intelligent Systems and Applications in Engineering, 12(20s), 61–77.

[15] B. Keerthiveena, T. Veerakumar, S. Esakkirajan and B. N. Subudhi, "Computer-aided diagnosis for Diabetic Retinopathy based on Firefly algorithm," 2019 11th International Conference on Advanced Computing (ICoAC), Chennai, India, 2019, pp. 310-315.

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 2 | Pages 669-681 | e-ISSN: 2347-470X

[16] Shaukat, N.; Amin, J.; Sharif, M.I.; Sharif, M.I.; Kadry, S.; Sevcik, L. Classification and Segmentation of Diabetic Retinopathy: A Systemic Review. Appl. Sci. 2023, 13, 3108.

[17] Subramanian, S.; Mishra, S.; Patil, S.; Shaw, K.; Aghajari, E. Machine Learning Styles for Diabetic Retinopathy Detection: A Review and Bibliometric Analysis. Big Data Cogn. Comput. 2022, 6, 154.

[18] Long, F., Sang, J., Alam, M.S. (2023). Machine Learning Based Diabetic Retinopathy Detection and Classification. In: Parah, S.A., Hurrah, N.N., Khan, E. (eds) Intelligent Multimedia Signal Processing for Smart Ecosystems. Springer, Cham.

[19] Zivkovic, M.; Bacanin, N.; Antonijevic, M.; Nikolic, B.; Kvascev, G.; Marjanovic, M.; Savanovic, N. Hybrid CNN and XGBoost Model Tuned by Modified Arithmetic Optimization Algorithm for COVID-19 Early Diagnostics from X-ray Images. Electronics 2022, 11, 3798.

[20] W. F. Almayahi, A. H. Najim and K. A. M. Al-Sharhanee, "Diabetic Net for Diabetic Retinopathy Image Classification Using Deep Convolutional Neural Network," 2023 IEEE 7th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), Purwokerto, Indonesia, 2023, pp. 152-156,

[21] Raichura, M., Chothani, N., & Patel, D. (2021). Efficient CNN-XGBoost technique for classification of power transformer internal faults against various abnormal conditions. IET Generation, Transmission & Distribution.

[22] V. Vijayan and S. A, "Survey on Deep Learning based Automated Systems for the Detection and Grading of Diabetic Retinopathy using Retinal Fundus Images," 2023 International Conference on Power, Instrumentation, Control and Computing (PICC), Thrissur, India, 2023, pp. 1-6.

[23] N. S, S. S, M. J and S. C, "An Automated Detection and Multi-stage classification of Diabetic Retinopathy using Convolutional Neural Networks," 2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN), Vellore, India, 2023, pp. 1-5.

[24] Batool S, Gilani SO, Waris A, Iqbal KF, Khan NB, Khan MI, Eldin SM, Awwad FA. Deploying efficient net batch normalizations (BNs) for grading diabetic retinopathy severity levels from fundus images. Sci Rep. 2023 Sep 2;13(1):14462.