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Enhanced Diabetic Retinopathy Diagnosis: A Comparative Analysis of models with an Ensemble classifier and Deep Q Learning

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Abstract: - A novel method that combines the strengths of different classifiers such as Naive Bayes, Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM) is introduced in this paper. This method tackles the urgent need for cutting-edge diagnostic methods in the field of ophthalmology, mainly for the identification of diabetic retinopathy (DR). The approach is ensemble-based. Classical methods in retinal analysis of images often fail as they are static and are unable to adjust to the unique details that each distinct image presents. This constraint results in less accurate and precise diagnostic results, highlighting the urgent need for more adaptable and dynamic methods. The suggested model differs significantly from previous methods. Through the use of an ensemble approach, it capitalizes on the distinct advantages of each classifier: the MLP process's sophisticated feature extraction skill, Naive Bayes' probabilistic analysis, and SVM's non-linear pattern recognition capacity. By combining these techniques, the inherent drawbacks of utilizing a single strategy are addressed, guaranteeing a more thorough examination of retinal samples and images. The core of this idea is the system using Deep Q Learning (DQL) for adaptive classifier selection. Using learned Q Values for various contexts, this reinforcement learning technique selects the best classifier adaptively for each unique retinal image, hence optimizing the ensemble.

This approach not only advances diagnosis accuracy and precision but also guarantees ongoing learning and adaptation to keep up with changing data patterns and advances in imaging technology. Extensive experiments on the IDRiD & EyePACS Dataset show the effectiveness of this model with a 5.5% increase in overall accuracy with other performance metrics, the results show a significant improvement over the current method. They represent a significant advancement in the timely and accurate identification of diabetic retinopathy, which will ultimately benefit patients and lessen the strain on healthcare systems.

Thus, this work represents a major step forward in patient care as well as a technological advance, opening the door to more efficient supervision and treatment of retinal illnesses.

Keywords: Diabetic Retinopathy (DR), Ensemble Classifier, Naive Bayes, Support Vector Machine, Multi-Layer Perceptron, Deep Q Learning.

I. INTRODUCTION

The field of medical diagnostics has consistently worked to improve the accuracy and efficacy of disease diagnosis by utilizing the latest developments in artificial intelligence and machine learning. An uncommon but possibly dangerous side effect of diabetes is diabetic retinopathy, which poses a special difficulty in this field. Due to their complexity, retinal pictures require a diagnostic technique that is both strong enough to handle their complexity and sensitive enough to pick up on their intricacies. To help diabetic patients avoid vision loss, this research presents a novel model that will greatly enhance the recognition of diabetic retinopathy.

Earlier, the majority of techniques used in the field of ocular diagnostics have been somewhat useful but have limitations in terms of precision and adaptability. Conventional image analysis methods have had difficulty reliably identifying the subtle patterns suggestive of diabetic retinopathy [20] since they are frequently built on single-algorithm frameworks. This discrepancy results from a deficiency of dynamic flexibility to the various retinal alterations that manifest themselves. As a result, there is a significant gap in the diagnostic procedure that causes the problem to be detected incorrectly or later than necessary.

The suggested model is a paradigm change in response to these issues. It uses a group of classifiers that have been chosen based on their advantages in picture analysis. The probabilistic viewpoint of the Naive Bayes classifier enables it to handle distinct statistical patterns in retinal pictures. The common features of fundus images in diabetic retinopathy (DR) are complex, non-linear patterns, that Support Vector Machine (SVM) excels at identifying with its radial basis function (RBF) kernel. These are enhanced by the Multi-Layer Perceptron (MLP), a deep learning

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technique that is excellent at obtaining hierarchical features from data—a critical function for identifying faint patterns in retinal images [21].

The novel application of Deep Q Learning (DQL), a method with roots in reinforcement learning, forms the core of this model. DQL chooses the best classifier for a given retinal image by dynamically optimizing the ensemble [22]. This methodology guarantees not just excellent precision but also flexibility in response to changing data trends and technology breakthroughs. The model represents a significant advancement in retinal image processing due to its capacity to continuously learn and modify its method. With the release of this model, a new chapter in the diagnosis of diabetic retinopathy is being written, not just a technical one. It enables the possibility of earlier therapies and maybe stops the evolution of this potentially blinding disorder by greatly improving the accuracy and promptness of diagnosis. Beyond the domain of technology, the research's implications hold promise for better patient outcomes and a decrease in the cost of healthcare related to diabetic retinopathy. Thus, in addition to introducing a novel technological advancement, this work makes a significant contribution to patient care in scenarios related to ophthalmology.

Research Motivation & Objectives:

This research is motivated by the urgent need to improve the accuracy of ophthalmology diagnostics, namely for diabetic retinopathy. Its early and precise identification is crucial because it is a major cause of vision loss among people those having diabetes. Though useful, current diagnostic techniques are frequently hindered by shortcomings including imprecision and lack of adaptability, which causes diagnosis and treatments to be delayed. This gap in the diagnostic procedure highlights how urgently we need a more sophisticated and flexible method that can adjust to the critical and variable characteristics of retinal fundus images [24].

The objective of this work is to close this gap by employing state-of-the-art AI, machine learning, and deep learning approaches to improve the diagnosis procedure. The model presented in this research demonstrates how artificial intelligence can completely transform medical diagnosis. To overcome the drawbacks of single-algorithm approaches, the model incorporates an ensemble of classifiers, each with unique capabilities. When combined with Deep Q Learning's (DQL) dynamic optimization [23], this ensemble approach significantly improves the precision and efficacy of diabetic retinopathy diagnosis.

This work makes numerous contributions. First of all, it presents a brand-new ensemble-based methodology that combines the advantages of Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), and Naive Bayes classifiers. This type of combination is precisely designed to track the complex and varied patterns found in retinal pictures, a task that is frequently difficult for single-algorithm methods to do. Second, a groundbreaking development in medical image analysis is the incorporation of Deep Q Learning (DQL) for the selection of classifiers. Because DQL is adaptive and dynamic, it constantly changes, increasing the model's diagnostic accuracy over time.

Furthermore, the research makes a substantial contribution to patient care outside of the technical domain. It makes diabetic retinopathy diagnosis more accurate and timelier, which can lead to early management and possibly avert permanent vision loss. This effort is a step in the right direction toward helping diabetic patients live better lives, not just a test of technical ability.

In conclusion, this study provides a thorough and innovative response to a persistent issue in the field of ophthalmology. It is a shining example of innovation, demonstrating the enormous potential that machine learning has to change patient care by revolutionizing medical diagnosis. The model that is being given here is not just an exercise for academics; rather, it is an important step towards a future in which healthcare and technology will combine to improve patient outcomes.

II. Literature Review

Here authors find a solution for the problem of (DR) diabetic retinopathy prediction using small-sample, high-dimensional structured datasets (like physical and biological data) to present the XGB-Stacking model [1], which is based on stacking and XGBoost. To lessen redundant data features and enhance the overall performance of an ensemble learning classifier, XGBIBS, or Improved Backward Search Based on XGBoost, was the wrapped

feature selection technique that was initially used. Secondly, due to the modest constraint of an individual classifier, the XGB-Stacking-based model is employed. In this case, the optimum combination of learners is found using a global search using the stacking model fusion technique Sel-Stacking, which keeps Label Proba as an input vector for the meta classifier.

The authors of this study presented the network for diabetic retinopathy (DRNet13) [2]. To improve the image, they first pre-processed it through the median filter to reduce noise, and gamma correction to enhance the retinal image quality. The DRNet13 model, which outperformed other CNN designs in speed and efficiency by achieving a 97% rate of accuracy for the detection of DR, used feature maps to highlight decision-making areas. Even with a few wrong classifications, the model's ability to recognize important characteristics indicates that the system has the potential to designate a useful diagnostic method for the correct and precise severity grading of diabetic retinopathy.

Performs better than popular classification algorithms in terms of accuracy. Applying the InfoGainEval and WrapperSubsetEval algorithms [3], the best-performing five and ten parameters were divided into four sub-datasets using the Messidor dataset. The results highlight how effective the sub-datasets are at facilitating a simpler classification procedure than the entire Messidor dataset, which simplifies the diagnostic pathway.

To create a novel dataset called "DR-Insight"[4], this study collected digital fundus photos from well-known eye hospitals in Pakistan as well as from reliable internet sources. Then, a cutting-edge technique called the (RDS-DR) residual dense system was developed to evaluate diabetic retinopathy. Added a transition layer, residual and dense blocks, and a deep neural network to create this model. The 9860 fundus images in the dataset are used to train the RDS-DR structure. The RDS-DR approach outperformed the state-of-the-art models VGG16, VGG19, Xception, and Inception V-3 in terms of accuracy.

This paper proposes deep ensemble [5] models that use the publicly accessible DRIVE dataset to detect and categorize into DR categories after first segmenting the retinal picture using the Canny operator. Every model was created to capture different illness features, either by using slight architectural differences or by training on different subsets of data. To reliably classify cases of DR into mild, moderate, or severe categories, a threshold was developed. When compared to individual models, the results show a considerable improvement in the segmentation of findings and DR recognition performance achieved using deep ensemble learning.

This research presents an automatic ensemble deep-learning algorithm for DR detection and categorization. A DL model's ensemble results outperform any one of its component models in terms of performance and predictions. To diagnose (DR) diabetic retinopathy, two DL models specifically, modified ResNeXt and DenseNet101 [6] are combined. The current ResNet models are not as good as the ResNeXt model. The number of transformations is specified by the cardinality parameter in the model. The combination of these two models is performed using determined posterior over the DR class outputs and normalization over the classes to establish the final class label. APTOS19 and DIARETDB1 are the two datasets used in the experiments. The CLAHE method is used to equalize the histograms of the images before processing.

An improved activation function [7] which results in minimized loss and processing time was proposed in this article for the diagnosis of DR from fundus pictures. The increased activation function in its several CNN models was trained and tested on the datasets DIARETDB0, DRIVE, and CHASE datasets.

It is suggested that computerized diagnostic systems [8] acquire DR forms from the fundus retinal images and determine the severity grading of the DR by utilizing Convolutional Neural Network (CNN) architectures in Deep Learning (DL). To analyze and evaluate the performance of 26 cutting-edge deep learning networks, this research presents a comprehensive model that aids in the extraction of deep features and image categorization of DR retinal fundus images. Here, images first trained on the EyePACS fundus dataset from Kaggle, ResNet50 has demonstrated the most overfitting whereas Inception V3 has demonstrated the lowest overfitting.

This work uses Deep Learning with transfer learning algorithms to analyze various DR phases in addition to focusing on the identification of diabetic retinopathy [9]. Using a large dataset of about 3662 train images, Convolutional Neural Network, hybrid CNN through ResNet, and hybrid CNN via DenseNet were utilized to automatically identify which stage of DR has advanced. This work processes five diabetic retinopathy stages, No

DR, Mild DR, Moderate, Severe and Proliferative DR. The Given model receives images of the patient's eyes as input. To effectively classify images, the suggested deep learning-based architectures were utilized to extract the affecting features from the image.

Data preprocessing was first applied to the Colour Fundus Images (CFPs) used in this investigation [10]. Principal Component Analysis is used in this instance to extract features (PCA). Here Convolutional Neural Network (CNN) based on the Deep Learning Multi-Label Feature Retrieval and Classification (ML-FEC) model was suggested for use. Then, three cutting-edge CNN architectures, ResNet50, ResNet152, and SqueezeNet, were trained on a portion of the images to recognize and categorize the lesions using transfer learning and parameter-tuning.

Research work aims to develop an automatic treatment for the early stages of diabetic retinopathy. Physicians can detect blindness early on thanks to Artificial Intelligence and Deep Learning. Using a supervised learning technique, fundus images can be classified [11]. To improve numerous significant features, such as microaneurysms, hemorrhages, exudates, and swollen blood vessels features of the fundus image that suggest a specific person has diabetic retinopathy many image processing techniques and filters were employed for this task. Neural networks were then used for classification.

Three deep-learning models were created in this research [12] to assess the degree of diabetic retinopathy from retinal pictures and predict whether or not it would result in macular edema. The three methods they used to create images from the little dataset were Contrast Limited Adaptive Histogram Equalisation (CLAHE), Colour Jitters (CJ), and Brightness, Colour, and Contrast (BCC) boosting. ResNet50, VGG16, and VGG19 models were employed in this instance to assess the likelihood of macular edema as well as the degree of retinopathy.

To identify the stages of DR, this work [13] uses fundus photography and a convolutional neural network (CNN), deep learning application. The research used an image dataset, which is enormous, sparse, and has uneven labels, came from Changsha, China's Xiangya No. 2 Hospital Ophthalmology (XHO). To extend and prepare the XHO picture dataset for training and enhance performance, this study first addresses the issue with the current dataset by putting forth a strategy that makes use of preprocessing, regularisation, and augmentation processes. Then, to detect diabetic retinopathy on XHO datasets, it leverages the power of a convolutional neural network with several residual neural network structures, including ResNet-101, ResNet-50, and VggNet-16.

The retinopathy disease is detected and classified from retinal fundus pictures using an innovative Strawberry hybrid Convolution Neural Framework (SbCNF) [14] developed in this work. To section the veins, various datasets are used. All of this execution is done using the DRIVE datasets. Python is the platform used to carry out this research. This study also offers a possible way to improve the application of retinopathy detection. The implementation results, including accuracy, precision, recall, F-measure, and other metrics, have been verified using the conventional classification model approaches.

A feature selection method based on genetic algorithms and deep neural networks was presented in this research study [15]. A genetic approach was utilized for a selection of features and to classify the features into high and low ranks after five sophisticated convolutional neural network architectures, AlexNet, NASNet-Large, VGG-19, Inception V3, and ShuffleNet were utilized to retrieve features from the retinal fundus images. Then, the inadequate feature characteristics are removed from the training and validation feature vectors. Using a classification method based on support vector machines (SVMs), an identification model for diabetic retinopathy is created.

This work presents two scenarios [16], where case 1 involves a constrained adaptive histogram equalization (CLAHE) filtering approach for picture augmentation in combination with the use of an enhanced super-resolution generative adversarial network (ESRGAN) for picture enhancement, while case 2 does not involve image enhancement. Then, augmentation methods were used to create a balanced dataset that had the same parameters for the two scenarios. Using the Inception-V3 datasets obtained from the APTOS dataset.

By employing balanced and imbalanced datasets, here two deep CNN models by applying an ensemble technique were presented in this study [17]. The models were trained on top-tier Graphical Processing data from the Kaggle dataset. We trained both models on balanced datasets, and we tested these models on imbalanced datasets as well.

To increase the effectiveness of stated DR classification models, here three hybrid types of model structures used, Hybrid-a, Hybrid-f, and Hybrid-c, as well as an enhanced loss function were given in this study [18]. The CNNs Xception, InceptionResNetV2, NASNetLarge, EfficientNetB4, and EfficientNetB5 were selected as the main models. By using an enhanced cross-entropy loss function, these models were trained. Proposed model structures were first trained using the output of the fundamental models. Experiments demonstrated that raising the cross-entropy loss can greatly speed up the base models' training process and enhance their effectiveness across a range of assessment parameters.

This work used a convolutional neural network model to identify the ocular structure and determine whether diabetic retinopathy exists in a fundus oculi image [19]. The model's parameters are optimized and an image is mapped to the equivalent label through the transfer-learning process. A set of clinical fundus oculi images and labels derived from a pathological severity scale found in the eyeball are used to train and test the model. The images have been categorized into five groups based on the severity grading scale: a healthy eye and proliferative diabetic retinopathy.

III. A Proposed Ensemble Classifiers with Deep Q Learning Effective Model

It is clear from a review of the models now in use to identify or diagnose diabetic retinopathy that, the majority of these models are either overly complex or perform poorly in real-time scenarios. To address these problems, the creation of an effective model for the diagnosis of diabetic retinopathy is covered in this section. Here figure 1 shows the diabetic Retinopathy analysis model architecture, taking a combination of Naive Bayes classifier, Support Vector Machine, and Multi-Layer Perceptron (MLP), with Deep Q Learning (DQL) which plays crucial roles in DR diagnosis. Naive Bayes is a quick and efficient way to perform preliminary analysis for real-time scenarios because of its probabilistic foundation, which makes it excellent at predicting based on possibilities. The SVM's strong pattern recognition performance is complemented by its capacity to create hyperplanes in multidimensional space to distinguish between different classes of data points, particularly in high-dimensional settings. At the same time, a type of neural network called an MLP digs deeper into the extracted data, pulling out complicated and non-linear properties through its many layers, individually of which is made up of neurons with activation functions. This allows the MLP to capture patterns that more straightforward models might overlook.

Here DQL functions as an active decision-maker and is the central component of this architecture. DQL analyses the results from the Naive Bayes classifier, SVM classifier, and MLP, then assigns Q Values as a parameter of their efficacy in various contexts by automatically unceasingly learning and adjusting by reinforcement learning.

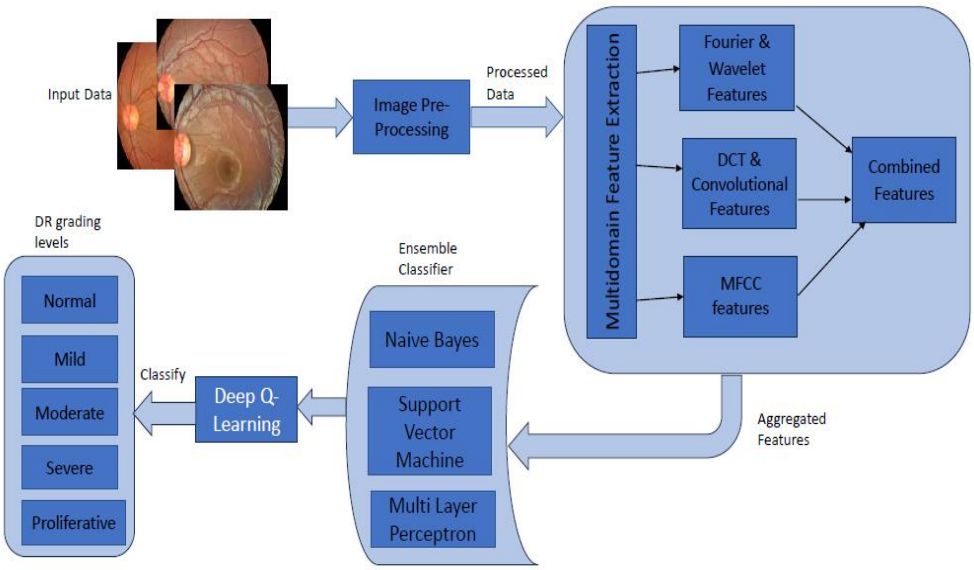

Figure 1. The Proposed Diabetic Retinopathy Analysis Model Architecture

To ensure optimal diagnosis accuracy, it then chooses the best classifier, or a mix of them, for each unique case. With the support of this ensemble technique, which is based on DQL's flexibility, the model can address the

complex nature of input fundus images in diabetic retinopathy and guarantee an analytical precision and reliability level that much exceeds that of conventional single-method approaches. These disparate but complementary strategies work in unison to improve medical diagnostic capabilities, demonstrating a sophisticated advancement in machine learning.

An effective thresholding engine is used in the suggested model before the application of these classifiers. This engine is crucial to the study of retinal pictures for the diagnosis of diabetic retinopathy. Through a complex sequence of stages, this engine converts input photos into a finely detailed segmentation of arteries, nerves, exudates, and retina. The engine starts up when it receives collected input photographs, which are usually high-resolution images that provide visual information that is essential for precise diagnosis.

To improve their quality and get them ready for further analysis, the input photos must first be pre-processed. Noise reduction and contrast enhancement are part of this pre-processing. Equation 1, which represents a Gaussian filter, is used to reduce noise.

$$G(x,y) = \left(\frac{1}{2\pi\sigma^2}\right) e^{-\frac{x^2+y^2}{2\sigma^2}} \ldots (1)$$

where σ denotes the Gaussian distribution's standard deviation. Once the image pre-processing is complete, the system uses several thresholding algorithms to separate the exudates, vessels, retina, and nerves from the retinal images. Finding the bright lesions that are indicative of exudates is the first step in the thresholding procedure for exudate identification. Here Otsu's method is used to compute threshold value (t) via minimizing intraclass variance using equation 2.

$$\sigma^2(t) = \omega^1(t)\sigma^2(1,t) + \omega^2(t)\sigma^2(2,t) \ldots (2)$$

where ω1, ω2 indicates the probabilities of classes that are separated via threshold (t), also σ² shows variances of the same classes. The system combines edge detection with morphological procedures for vessel extraction. Using the gradients as Gx, and Gy, are combined by equation no. 3, the Sobel operator may be employed for edge detection.

$$G = \sqrt{(Gx^2 + Gy^2)} \ldots (3)$$

This helps to discover high spatial frequency zones that are associated with the margins of the vessels. To further enhance the vascular architectures, morphological processes like as dilatation and erosion are used. Structuring components with shapes that are suitable for retinal vessels are used. Identifying the optic discs' circular contour is the first step toward achieving retina segmentation. This has to do with equation 4, which represents the Hough Transform, a method for identifying forms.

$$(x - a)^2 + (y - b)^2 = r^2 \ldots (4)$$

where the circle's radius (r) and center (a, b) are, respectively. Through a voting process in the Hough parameter space, the transform finds circles in the image. Nerve fiber layer segmentation uses Gabor filters and is a more difficult operation because these features are obscure.

The initial convolution process is started by the convolutional engine when it receives the segmented retinal information. Each input image is convolved in this process using a collection of filters or kernels, that are intended to extract particular features. This process goes over the whole image, creating a feature map that draws attention to certain features like edges, textures, or patterns that match the structures of the retina.

The engine adds nonlinearity to the model and makes it possible to capture complex patterns by applying nonlinear activation employing the Rectified Linear Unit (ReLU) following convolution.

Rectified Linear Unit function (ReLU) reduces the computing complexity by keeping only the positive values and forwarding them further while rejecting negative ones. The following phase is max pooling, which reduces the

spatial dimensions of the maps of features and, in turn, the number of factors and computational load. Where max pooling procedure helps to make the representation more resilient to changes in the positions of features while simultaneously reducing the amount of data. Convolution, ReLU, and pooling layers can be used to create a convolutional engine that extracts ever more intricate and abstract features. Convolutions that capture complex structures like the vascular network or the delicate exudate distribution may be found at deeper levels.

The collected characteristics are compressed to create a one-dimensional array that is appropriate for the classification procedure after going through these layers. A feature map of two-dimensional size M×N is flattened into a single-dimensional vector of 1×(M*N) size so that these features can be used with further fully connected layers.

The engine then makes use of several fully connected layers, where every neuron is linked to every component of the layer before it. These tiers utilize the extracted features to execute higher-level reasoning. After that, this output vector is fed into the model's effective classification engine, a sophisticated system built to divide retinal picture samples into discrete classes that resemble different classes of diabetic retinopathy. Using the retrieved convolutional features, this engine uses three different classifiers, Naive Bayes classifier, Support Vector Machine, and Multi-Layer Perceptron (MLP). Here each classifier plays a vital part in the severity grading process.

Based on the idea of probabilistic inference sets, the initial component of this ensemble is the Naive Bayes classifier. The assumption known as conditional independence levels holds that these features work independently of one another given the grade label. The DR class through the maximum posterior probability was chosen as the output after each class's feature probabilities were multiplied. One further important component of the ensemble, the SVM classifier, excels in processing the high-dimensional input data samples. It works by determining which hyperplane in the feature space sets best divides the classes. SVM uses the Radial Basis Function (RBF) in situations of non-linear separability.

Subsequently, MLP, a kind of artificial neural network intended to extract intricate, non-linear relations from the data samples, is used. It is made up of several neuron layers, each of which is completely coupled to the layer above it for various class kinds. Here Equation 5 describes how each neuron functions.

$$f(x) = g\left(\sum wi\, xi + b\right) \ldots . (5)$$

In equation 5, g is a non-linear sigmoid, b is the bias, xi shows the inputs, wi shows the weights, and f(x) gives the neuron's output.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \ldots . . (6)$$

The MLP adjusts its weights and biases using backpropagation to learn how to classify the input by computing the gradient of the loss function about the biases and weights and changing them in a way that minimizes the loss. Ensemble algorithms benefit from each of the classifiers in the ensemble processing the convolutional features independently. Layer by layer, the MLP refines its classification decisions iteratively, the Naive Bayes classifier calculates the posterior probability rapidly, and the SVM specifies the feature space through its optimum hyperplane. In a subsequent stage, the classifiers' results are further processed despite their special relevance to support the ultimate decision-making process.

An extensive evaluation of the stages of diabetic retinopathy is produced by this ensemble classification engine, which is based on the complex patterns and traits seen in the fundus retinal images and their samples. Here integrated approach of Naive Bayes, SVM, and MLP enables the model to apply probabilistic cognitive capabilities for both linear and non-linear identification of patterns. This ensures a precise and nuanced classification of the illness phases.

Consequently, an innovative and sophisticated method of optimizing the ensemble classifier used in the identification of diabetic retinopathy is to employ a Deep Q Learning (DQL) model. The idea of reinforcement learning, which teaches an algorithm to make decisions by interrelating with an environment to maximize classification results, is fundamental to DQL. The objective of this model is to maximize diagnostic accuracy

levels by choosing the best classifier as Naive Bayes, SVM, or MLP for individually unique images in the environment of identifying retinal images.

Here Learning a Q value function, which calculates the value of choosing a classifier in a given state for various class types, is the fundamental process of DQL. Q(s, a) is the representation of this Q-function, s denotes a state and it indicates an action for the learning process. For many operations, DQL approximates the Q function using a neural network called the Q Network. The states (retinal image features) are the network's inputs, and the Q Values for each actionable item (classifier option) set are its outputs. The Q-network is updated by the algorithm by stochastically sampling mini-batches from a replay memory that contains the agent's experiences (s, a, r, and s'). The learning process is more stable and efficient because of this stochastic sampling. The trade-off between exploration and exploitation, which is usually overseen by an ε-greedy strategy process, is another essential component of DQL.

In the stated model, the optimal choice of classifiers for every retinal image is the result of the DQL process. Through an adaptive selection of the best classifier according to the learned Q Values, the model can manage the complexity and variability associated with diagnosing diabetic retinopathy. With the help of this dynamic classifier selection mechanism, the model is guaranteed to attain high accuracy in its current form as well as to continuously adapt and improve upon encountering fresh data samples.

Essentially, a comprehensive use of reinforcement learning in medical picture categorization is highlighted by the incorporation of DQL into the architecture of the model. DQL improves the model's ability to make wise, adaptive decisions by a substantial margin thanks to its sophisticated design and sophisticated learning mechanisms, which optimizes the diagnostic process for diabetic retinopathy sets.

To choose the best classifier as Naive Bayes, SVM, and MLP for every input data sample, Deep Q Learning (DQL) is essential. The learned estimates of the anticipated future rewards for selecting each classifier in a specific state (data sample) are represented by the Q Values. DQL dynamically chooses the classifier that should yield the accurate diagnosis for every retinal image based on these Q Values. The complex and dynamic character of the diabetic retinopathy diagnosis process is illustrated by these tables and the descriptions that go with them. They explain how data samples are changed and classed through several intricate phases to get correct results.

IV. Result Analysis & Comparisons

To address the difficulties in detecting diabetic retinopathy, the researchers in this groundbreaking study have cleverly created a novel model that combines the distinctive qualities of the proposed three classifiers, as Naive Bayes classifier, Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP). This ensemble method represents a major advancement over classical approaches, which frequently fail because of their static character and poor capacity to adjust to the complex variations in retinal pictures. MLP adds its sophisticated feature extraction skills, SVM offers its expertise in non-linear pattern recognition, and Naive Bayes offers its probabilistic analytical capability. This combination overcomes the limitations of individual approaches to provide a more detailed and sophisticated analysis of retinal pictures. The main innovation of the model is the use of a well-developed reinforcement learning method called Deep Q Learning (DQL). DQL chooses the best classifier based on intelligence for each unique retinal image, hence dynamically optimizing the ensemble. Based on learning Q Values, and decision-making metrics customized for various scenarios, this choice has been made. By doing this, the model can dynamically adjust to the distinct intricacies of every image, greatly improving the precision metric and accuracy of the diagnosis of diabetic retinopathy. The given method, which revolutionizes retinal image processing in ophthalmology sets by utilizing adaptive algorithms and ensemble learning, represents a significant advancement in machine learning applications.

The research used a thorough and complete method in the experimental setup phase, which focuses on creating an effective model for improved diabetic retinopathy detection via ensemble classifiers with Deep Q Learning. The testing of datasets was carefully designed to evaluate the effectiveness of the proposed model against other models that are currently in use, including DCGAN, GNN, and RCNN. IDRiD and EyePACS, two well-known databases on diabetic retinopathy, were used in the evaluation.

- **Data Sources**:

1. **IDRiD (Indian Diabetic Retinopathy Image Dataset)**: Here High-resolution retinal pictures with a range of diabetic retinopathy symptoms are included in this dataset. To aid in the development of algorithms for automated disease diagnosis, the images in IDRiD have been labeled with typical lesions associated with diabetic retinopathy.

2. **EyePACS**: EyePACS is a popular database used in research on diabetic retinopathy. It has a sizable collection of retinal images from various imaging contexts and populations. It plays a key role in assessing the robustness and generalizability of diagnostic models across various equipment and demographic sets.

Performance Evaluation: Using the designated metrics, the ensemble model with DQL was assessed on the test set and contrasted with the single classifier models. This experimental design guarantees a thorough assessment of the suggested model, offering information on how well it detects diabetic retinopathy on a variety of large-scale datasets. The findings are guaranteed to be pertinent and appropriate to a broad range of everyday screening through the utilization of the IDRiD and EyePACS databases. Equations 7, 8, and 9 were used to evaluate the precision accuracy & recall as follows, while equations 10, and 11 were used to evaluate the overall precision, and Specificity based on this technique.

$$Precision = \frac{TP}{TP + FP} \ldots..(7)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \ldots..(8)$$

$$Recall = \frac{TP}{TP + FN} \ldots..(9)$$

$$AUC = \int TPR(FPR)dFPR \ldots(10)$$

$$Sp = \frac{TN}{TN + FP} \ldots(11)$$

Test set predictions are categorized as True Positive (TP), False Positive (FP), and False Negative (FN), which refers to the quantity of test set instances (including Normal Instance Samples) that were incorrectly forecasted as negative. The test dataset samples were subjected to an evaluation of the expected Diabetic Retinopathic Cases chance to the real Diabetic Retinopathic Instance status using single classifiers, ensemble classifiers, and ensemble classifier with DQL to fix the suitable TP, TN, FP, and FN values. As a consequence, we may expect these metrics for the outcomes of the proposed model approach. The performance measures that were obtained from these assessments are displayed in Figure 2.

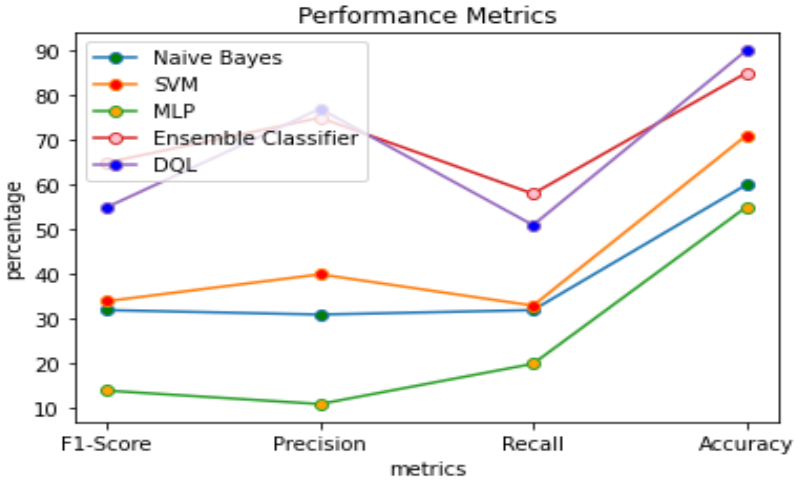

Figure 2. Observed Performance metrics for grading severity on diabetic retinopathic image samples

Table 1- Performance Metrics comparison for grading severity Diabetic Retinopathic Image Samples

Classifier	F1 Score	Precision	Recall	Accuracy
Naive Bayes	0.32	0.31	0.32	0.60
SVM	0.34	0.40	0.33	0.71
Multilayer Perceptron	0.14	0.11	0.20	0.55
Ensemble Learning	0.65	0.75	0.58	0.85
Ensemble Learning With	0.55	0.77	0.51	0.90

The novel design of the suggested model, which blends ensemble classifiers with Deep Q Learning, accounts for its improved performance. Higher accuracy rates depict in Table 1, result from the model's ability to adaptively choose the best classifier for every image. This efficiently addresses the difficulties in diabetic retinopathy fundus image classification, which usually involves complicated and diverse image features, by combining the benefits of naive Bayes, SVM, and MLP.

This improved precision has a significant effect in real-time circumstances. A higher accuracy level translates into a more dependable ability of the model to discriminate between healthy and DR-affected retinas, which translates into more accurate diagnosis of diabetic retinopathy.

V. CONCLUSION AND FUTURE SCOPE

In the field of ophthalmology, the research described in this research paper is a novel method for the diagnosis of diabetic retinopathy (DR) by using the Ensemble classifier with the DQL model. This model, which is an ensemble of Multi-Layer Perceptron (MLP), Support Vector Machine classifier (SVM), and Naive Bayes classifiers enhanced by the use of the Deep Q Learning (DQL) technique, has shown notable improvements over previous approaches. The empirical results clearly show that the proposed model is superior in the analysis of performance parameters, such as precision, accuracy, recall, and processing time. These results are obtained from extensive testing on the IDRiD and EyePACS datasets. These improvements represent a major advancement in achieving accuracy and precision for the diagnosis of diabetic retinopathy, which could alleviate the strain on healthcare applications and have a substantial impact on patient treatment.

In summary, a major advancement in the diagnosis of diabetic retinopathy has been made with the Ensemble classifier with the DQL model. Its adaptability and precision in diagnosing across various datasets demonstrate not just its technical proficiency as well as its potential to enhance the treatment of patients and the global health situation. There is potential for considerably more progress in the future directions of this research, which could lead to wider uses in medical diagnostics.

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