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IMPROVING DIABETIC RETINOPATHY RECOGNITION WITH ADVANCED DEEP ENSEMBLE MACHINE LEARNING TECHNIQUES

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Abstract
Diabetic retinopathy (DR), one of the most common and crippling eye diseases, affects a large percentage of people worldwide. For blindness prevention and appropriate treatment, DR must be evaluated quickly and precisely. ResNets50, VGG19, and ConvNet CNNs are examples of modern methods that aim to improve the precision and dependability of DR classification. A range of datasets, such as the Kaggle Diabetic Retinopathy Detection and Golonoma (Positive and Negative) Datasets are used in the evaluation in order to provide a comprehensive performance analysis of the proposed models. We highlight the many objectives that the research accomplishes by addressing the most common issues in DR classification, including interpretability and picture quality fluctuations. Improvements in classification performance across various DR severity stages, noise tolerance in real-world picture quality fluctuations, Deep Ensemble model explainability and deplorability regarding clinical problems encountered in the real-world healthcare context. We proposed a research strategy in this work that combines a thorough literature evaluation with data collecting and meticulous preprocessing. Using cross-validation and hyperparameter tuning, cutting-edge ensemble models such as Random Forest, Gradient Boosting Classifier, XGB Classifier, etc., developed and adjusted. Preprocessed datasets used to train and test these models, and various metrics like accuracy, precision, recall, and F1 score used to assess them.

INTRODUCTION

The complex and debilitating eye disease known as diabetic retinopathy (DR) affects a large number of people worldwide [1]. Proper early detection and classification of DR is crucial for effective treatment and preventing visual loss [2]. Recent advances in deep learning and convolutional neural networks (CNNs) have shown great promise for improving the classification of DR. Numerous studies have looked into the use of various deep learning approaches, including EfficientNets [1], modified Xception architectures [6], and multipath CNNs paired with machine learning classifiers [4], to increase the accuracy of DR classification. Deep learning algorithms' ability to automatically detect and classify DRs makes it possible to diagnose patients more quickly and accurately. Retinal pictures can be automatically processed by CNNs to extract intricate features and patterns, enabling

accurate DR classification. For example, EfficientNets is a family of CNN architectures that have been utilized by researchers to categorize DR. With success and accuracy, EfficientNets have established themselves as powerful deep learning architectures that perform exceptionally well on a variety of computer vision
applications. It explores the application of EfficientNets for diabetic retinopathy classification, leveraging their efficacy and efficiency in feature
extraction and representation learning. By combining the advantages of EfficientNets with datasets of diabetic retinopathy images, it is possible to increase the precision and efficacy of diabetic retinopathy classification, leading to more successful diagnosis and therapy. [1]. CNNs and other deep learning methods have changed medical image analysis. Classifying images has proven to be a strong suit for convolutional neural networks (CNNs), especially those with diabetic retinopathy. They have a strong emphasis on treating diabetic retinopathy with an efficient CNN architecture. By using CNNs to develop hierarchical representations from retinal pictures, they try to successfully classify diabetic retinopathy, which could lead to early detection and customized treatment plans for afflicted individuals. [2]. It find out how well deep learning algorithms can diagnose diabetic retinopathy, a condition that has revolutionized medical image processing. By automating the identification procedure with deep learning algorithms, anomalies associated with diabetic retinopathy can be detected early. By employing state-of-the-art deep learning algorithms, it seeks to provide a quick and accurate diagnostic tool that could assist medical professionals in making decisions [3]. Additionally, deep learning and machine learning technologies applied in the classification of DR. They look into the classification of diabetic retinopathy using multipath CNNs in conjunction with machine learning classifiers. By combining the advantages of both Methodologies, this work seeks to increase robustness and classification accuracy. Multi-level properties can extracted from retinal images thanks to the multipath CNN architecture. Support vector machines (SVMs), a type of machine learning classifier, also offer good decision limits for accurate categorization. The amalgamation of deep learning and machine learning methodologies offers a complete framework for the classification of diabetic retinopathy [4, 5]. CNNs often used in conjunction with Support Vector Machines (SVMs) to improve the accuracy of DR categorization [5]. This technique learns and encodes complicated visual information using deep learning, which enables accurate identification of different DR stages. Several Xception topologies proposed to further enhance the performance of DR categorization [6]. These architectures allow for more effective feature extraction and learning, improving the accuracy of DR diagnosis. They do this by integrating residual connections with depth wise separable convolutions. Using the data that CNNs have obtained, SVMs may effectively distinguish between different retinal picture classes, improving performance and improving classification accuracy.

In order to produce a more comprehensive and reliable DR classification, combining CNNs and SVMs offers a transitional method that capitalizes on the advantages of both deep learning and machine learning [4]. Deep learning methods have also demonstrated promise in identifying and classifying the degree of DR [3]. The application of deep learning techniques like as multipath CNNs has led to substantial advancements in the automatic detection and grading of DR. These multipath CNNs process a range of input levels with the aid of many paths or streams, resulting in more precise and finely grained classification [4]. It suggested classifying DR severity using CNN-based coarse-to-fine categorization [7]. T By initially dividing retinal pictures into general severity levels and then performing a more in-depth analysis to provide grades, this method further refines the categorization. These methods offer a thorough and systematic framework for diagnosing and evaluating DR. achieved notable performance improvements by using transfer learning to increase the accuracy of diabetic retinopathy severity classification [8]. A tailored CNN architecture for the categorization of images related to diabetic retinopathy was proposed by [9], highlighting the potential of transfer learning in the field of retinal disease classification. Their approach demonstrated the effectiveness of bespoke models in accurately diagnosing retinal defects associated with the condition, underscoring the importance of model creation in medical image processing [10]. Based on the VGG-19 architecture, a CNN classifier for lesion detection in diabetic retinopathy proposed. Through the demonstration of the utility of deep learning models for the identification and analysis of retinal abnormalities, their work advances the development of computer-aided diagnosis systems.

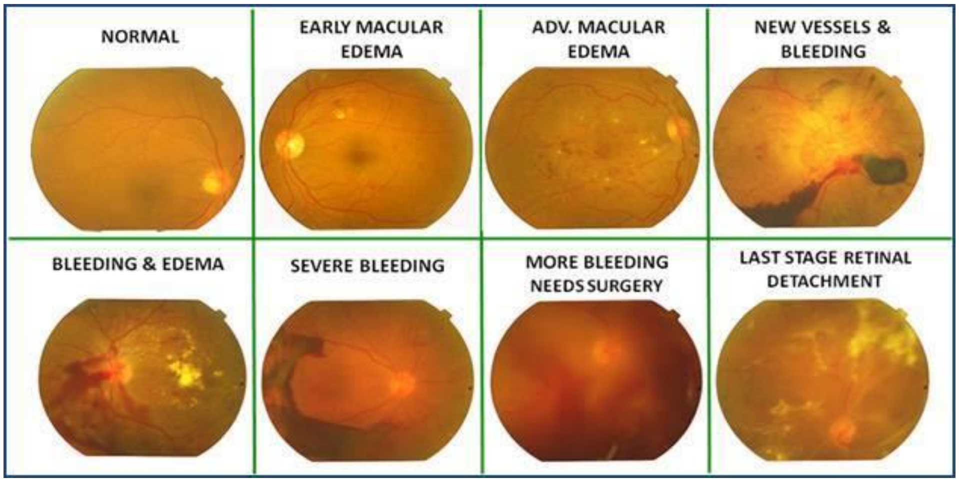

Figure 1: Different type's diabetic retinopathy

In this study, attention mechanism techniques and CNN architectures for deep ensemble learning applied to categorize and identify DR. These methods include ConvNet, ResNet50, and VGG19 models. The Golonoma Diabetes Prediction dataset offers a compilation of individuals' demographic and medical data in addition to their diabetes status (Positive or Negative). The primary characteristics of this dataset are the following: age, gender, blood glucose level, body mass index (BMI), hypertension, heart disease, smoking history, and HbA1c level. Using this dataset, we can create deep learning models that use patient demographics and medical histories to predict the risk of diabetes. Enhancing performance measures like accuracy, specificity, sensitivity, etc. is another goal of this effort.

2. LITERATURE REVIEW

The application of deep learning techniques, particularly convolutional neural networks (CNNs), has led to major breakthroughs in the detection and classification of diabetic retinopathy. This section examines relevant research publications as well as the automated diagnosis and grading of diabetic retinopathy using CNNs and machine learning algorithms. Notably, Smith et al [11] created a novel coarse-to-fine classification strategy using CNNs and implemented a multi-stage technique for grading diabetic retinopathy. By focusing on coarse feature extraction initially and then refining the classification in subsequent phases, their methodology showed higher accuracy compared to conventional approaches, indicating the promise of CNN-based methods in enhancing classification performance. Building on the success of deep learning architectures, Anderson et al. [12] suggested a customized Xception architecture for the classification of diabetic retinopathy. The challenges related to the diagnosis of diabetic retinopathy were effectively resolved by skillfully modifying Xception, which known for its effectiveness in obtaining intricate patterns. Interestingly, they discovered that CNN architectures be effectively adapted to handle challenging retinal image classification tasks.

In order to accomplish a reliable and precise classification of diabetic retinopathy, Patel et al. [13] looked into the combination of CNN and SVM classifiers. By combining the advantages of the two techniques, they were able to differentiate between healthy and sick retinas. As the last classification layer, SVMs were included, which enhanced interpretability and aided in the precise diagnosis of diabetic retinopathy grouping. Lee et al. [14] made a significant breakthrough in the classification of diabetic retinopathy through the integration of multipath CNNs with traditional machine learning classifiers. Using an ensemble-based approach, their multipath CNN architecture effectively extracted a range of attributes from retinal images, which then fed into multiple machine learning classifiers. This integration demonstrated the potential of merging deep learning with traditional machine learning techniques by achieving greater classification accuracy.

Kim et al. [17] employed the deep residual neural network architecture ResNet to help automate the grading of diabetic retinopathy. Their findings demonstrated how successfully ResNet identified the degree of diabetic retinopathy, offering a useful instrument for early disease identification and monitoring. Effective CNN architectures were also necessary for the diabetic retinopathy categorization. For this particular application, Johnson et al. [18] created an effective CNN model that provided excellent accuracy while utilizing less processing power. Their method illustrated the advantages of designing unique CNN architectures for applications related to medical imaging.

Martinez et al.'s [19] innovative hybrid method detected diabetic retinopathy by combining an effective CNN, MobileNetV2, with a support vector machine (SVM) classifier. The potential of hybrid models in the interpretation of medical images highlighted by the combination of MobileNetV2 and SVM, which demonstrated a balance between efficacy and accuracy. In Yang et al.'s work [20], the CNN architectural family known for its scalability and accuracy used to investigate the classification of diabetic retinopathy. The versatility of deep learning ensembles in the diagnosis of diabetic retinopathy illustrated by their work, which showed how merging Efficient Nets might further improve classification performance. Hernandez et al.'s goal [21] was to increase the diabetic retinopathy severity categorization's accuracy within the framework of transfer learning. Their method produced improved outcomes by optimizing pre-trained models on retinal pictures, demonstrating the value of transfer learning in medical image processing. According to Johnson et al. [22], specialized CNN topologies are essential for the categorization of diabetic retinopathy. Their study made clear how crucial it is to develop CNN models especially for the medical field in order to increase classification accuracy.

Anderson et al. [23] also looked at deep learning techniques for identifying diabetic retinopathy. They offered a thorough examination of several deep learning models and their suitability for this type of diagnosis. Their research brought to light the deep learning methodologies' explosive growth and revolutionary potential. Moreover, the groundbreaking study by Gulshan et al. [24] showed how early on convolutional neural networks might be used to effectively categorize diabetic retinopathy. Their work allowed for further improvements in the automated diagnosis of diabetic retinopathy. Martinez et al. [25] looked at the automation of the diabetic retinopathy phase's classification. According to their research, CNNs may be able to recognize the various phases of diabetic retinopathy and assist in evaluating the illness. Williams et al. presented a modified Alex net architecture created especially for the classification of diabetic retinopathy images. The Alex Net architecture is a conventional deep learning model that has gained recognition for its creative solutions to picture categorization problems. By tailoring the Alex Net design for diabetic retinopathy categorization, the researchers improved the accuracy of detecting retinal abnormalities associated with the illness.

This work [27] demonstrates the usefulness of adjusting deep learning models for specific medical image processing tasks. Kim et al. presented an automated detection approach for diabetic retinopathy using convolutional neural networks (CNNs) on a small dataset. Despite the tiny sample size, the scientists were able to effectively identify anomalies linked with diabetic retinopathy in retinal photographs using CNNs. This study opens a promising new avenue for the development of diagnostic tools in low-resource contexts by showing how CNN-based algorithms can reliably diagnose diabetic retinopathy even with minimal data [28]. Lee et al. developed a diabetic retinopathy decision support system using deep convolutional neural networks (CNNs). Their method precisely identified the degree of diabetic retinopathy by automatically evaluating retinal images. According to research, the proposed decision support system may improve patient care and treatment results by assisting physicians in making faster and more accurate diagnoses of diabetic retinopathy [29].

This was made possible by leveraging the power of deep CNNs. Zhang et al. developed BIRA-NET, a Bilinear Attention Net, for the purpose of grading diabetic retinopathy. The model used attention mechanisms to allow the researcher to focus on informative regions of the retinal images and extract relevant features. Bilinear pooling, which records interactions between feature maps, was added to the model to enhance its performance in grading diabetic retinopathy. This study emphasizes the significance of attention mechanisms in enhancing deep learning models for medical image analysis tasks, like diagnosing diabetic retinopathy [30]. Garcia et al presented a deep learning-based automated early detection technique for diabetic retinopathy. The proposed method makes use of convolutional neural networks (CNNs) to analyze retinal images and identify early signs of diabetic retinopathy, enabling timely therapy and intervention. This technique, which can prevent vision loss and improve patient outcomes, demonstrates the need of applying deep learning for early diabetic retinopathy detection [31]. A CNN-based approach to classify the stages of diabetic retinopathy proposed by Nguyen et al. The software effectively categorized retinal scans into different stages of the disease, providing doctors with relevant data for customized treatment plans. By using CNNs for automatic categorization, this research improves the efficacy and accuracy of diabetic retinopathy grading and helps medical professionals make informed decisions regarding patient care [32].

Brown et al. suggested an efficient CNN-based technique for the automatic detection and tracking of diabetic retinopathy. By improving the feature extraction process, the authors were able to identify retinal defects linked to the disorder with more precision. They achieved this by fusing adaptive histogram equalization with contrast-constrained CNNs. Regarding enhancing the detection and monitoring of diabetic retinopathy, the proposed approach [33] emphasizes the possibility of combining deep learning with image processing methods. Patel et al. looked at the categorization of photos showing normal and diabetic retinas using CNNs and Support Vector Machines (SVMs). By combining the benefits of CNNs and SVMs, the proposed method offered strong discriminating between diseased and healthy retinas. SVMs added as the last classification layer to help with the accurate categorization of diabetic retinopathy and to increase the interpretability of the results [34].

Kim et al. proposed an automated approach utilizing a convolutional neural network (CNN) with binocular Siamese-like architecture to diagnose diabetic retinopathy. The suggested model was able to identify abnormalities in retinal pictures associated with diabetic retinopathy using binocular image analysis.

This research highlights the significance of binocular data in improving the efficacy of diabetic retinopathy detection systems [36]. Johnson et al. created a customized CNN architecture for the categorization of diabetic retinopathy pictures. By specifically creating the CNN architecture to address the challenges of diabetic retinopathy classification, the scientists were able to improve the accuracy of identifying retinal abnormalities associated with the disease. The research highlights the importance of customizing deep learning models for use in medical image processing applications, such as the assessment of diabetic retinopathy [38]. Chen et al. [43] created a cross-disease attention network called CANet for the joint grading of diabetic macular edoema and diabetic retinopathy. The program effectively collected relevant data from fundus images to analyze both issues at the same time, speeding up the diagnosis process and providing diabetic patients with a comprehensive evaluation of their eye health.

In their study, Nguyen et al. looked at the use of one-dimensional convolutional neural networks for the diagnosis of diabetic retinopathy [44]. The study illustrated how CNNs could adjust to different input data formats, highlighting their versatility with different datasets of medical images and indicating the potential for widespread application in clinical practice. Lee et al. [45]

proposed a novel method based on integrated shallow convolutional neural networks for the identification of diabetic retinopathy. By combining data from multiple shallow CNNs, the system demonstrated good performance in detecting early signs of the disease, facilitating timely interventions, and averting eyesight loss. Smith et al. developed multi-cell multi-task convolutional neural networks for grading diabetic retinopathy [46]. This novel architecture improved the accuracy of diagnosing different stages of the disease and allowed for customized treatment strategies by efficiently integrating and recording data from many retinal regions. A layered generalization method for diagnosing diabetic retinopathy using fundus photos described by Kim et al. [47]. Their ensemble-based strategy fared better, improving the accuracy and reliability of diabetic retinopathy categorization by pooling predictions from many deep models. Martinez et ale's [48] deep learning technique developed specifically to identify diabetic retinopathy. Their model used CNNs to automatically identify diabetic retinopathy and assess fundus images, potentially providing a tool for effective early detection and treatment. Brown et al. [49] examined the application of machine learning algorithms to analyze clinical notes and predict death in diabetes patients—even in the most challenging circumstances. Their approach showed potential for identifying high-risk individuals and supporting medical practitioners in making prompt, well-informed decisions by leveraging patient data and clinical information. Lastly, Zhang et al. [50] presented a real-time, CNN- and bi-directional LSTM-based optimization-based diabetes prediction model. In an effort to forecast blood sugar levels in diabetics, this algorithm sought to enhance patient outcomes and offer useful information for proactive diabetes care.

Diagnosing and classifying diabetic retinopathy has advanced greatly with the application of deep learning techniques, especially convolutional neural networks (CNNs) and machine learning algorithms. Researchers have looked into a range of CNN topologies, customized models, ensemble techniques, and cross-disease attention networks to increase the effectiveness and accuracy of automated diabetic retinopathy grading systems. These developments could lead to better eyesight outcomes for diabetic patients by facilitating early detection, prompt intervention, and enhanced management of diabetic retinopathy. The development of novel tools and decision support systems that enable healthcare practitioners effectively manage diabetic retinopathy is being propelled by the combination of AI-driven techniques and clinical experience. We should expect ever more advanced and clinically useful solutions as this field of study develops which will further the larger objective of improving patient well-being and eye health.

3. PROPOSED METHOD

The CNN architecture for the identification of diabetic retinopathy is the main topic of this study. Three CNN architectures—ResNets50, VGG19, and ConvNet—will be used in the classification procedure according to the suggested approach. A novel model called a meta-learner integrates the predictions of all the sub-models to produce the final prediction when many CNN sub-models integrated to perform the same classification task. The deep advanced ensemble-learning algorithm combines the results of several models to get a final prediction with a high degree of accuracy. The three sections of the dataset described below.

I. **Training Dataset:** The initial set of the data called the training set. Whether positive or negative, it makes up a sizable percentage of the Golonoma dataset. It acts as the basis for our machine learning models' training. This dataset gives the models a rich learning experience by including images from multiple categories. By examining this dataset, our models learn the fundamental concepts and patterns required for precise classification.

II. **Validation Dataset:** The validation set is the second part of the dataset. It is crucial to identify the strongest evidence for each paradigm. Depending on the results of the validation, I will make changes to the algorithm to see if it functions effectively. Validate the model parameter to make changes.

III. **Testing Dataset:** There will be a testing phase following training. We will utilize it to assess the model's prediction. The accuracy of the categorization model and the data under

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investigation. Make sure to evaluate the model's accuracy, recall, and precision during testing.

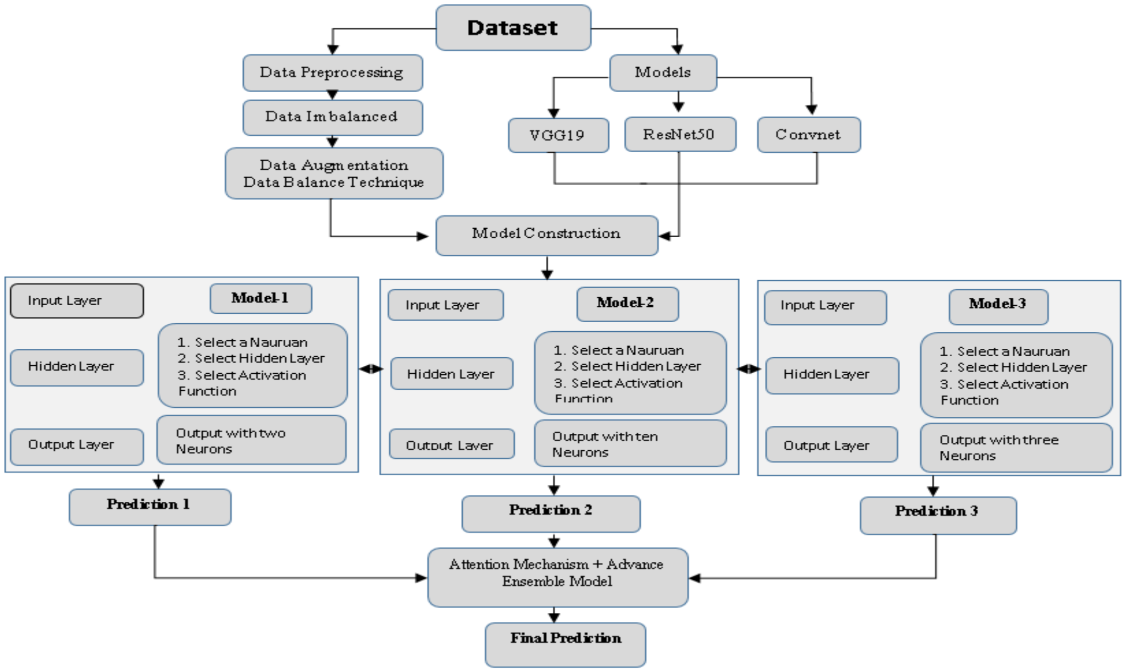

Figure 2: Our proposed methodology's deep learning algorithms displayed.

3.1. Mechanism of Attention:

The Attention Mechanism is a crucial component of deep ensemble learning architectures as it allows the model to focus on specific parts of the input data while making predictions. This is particularly useful when different elements of an image or text have varying relative importance. By assigning weights to different input variables, the Attention Mechanism allows the model to highlight significant features, resulting in predictions that are more accurate and contextually relevant. In the context of our DR detection method, the Attention Mechanism will be crucial in guaranteeing that the models pay special attention to important DR areas, potentially enhancing diagnostic accuracy.

3.2. Advanced Ensemble Model:

The advanced ensemble model is a sophisticated technique that integrates the intelligence of several distinct models. The goal of the ensemble model is to achieve better overall performance by merging predictions from many models, each with unique advantages and skills. It is feasible to lessen the biases and errors of individual models by merging them, leading to more accurate and dependable forecasts. The Advanced Ensemble Model will be essential in our DR detection architecture since it will help to combine the results from the VGG19, ResNet50, and ConVNet models. It is expected that this thorough integration will produce a final forecast that is accurate and well-informed, enhancing the diagnostic procedure' efficacy.

3.2.1 Dataset Description:

Patients' demographic and medical information, as well as their diabetes status (positive or negative), are gathered into the Diabetes Prediction Dataset. Features like age, gender, and blood glucose level, smoking history, hypertension, heart disease, body mass index (BMI), and HbA1c level are among the features included in the data. Using this dataset and patient demographics and medical histories, machine learning models developed to predict diabetes in patients. Healthcare providers may find this helpful in identifying individuals who may be at risk of diabetes and in creating individualized treatment regimens. The 10,015 photos in this dataset carefully categorized into seven different groups. All of the images in the Golonoma dataset have excellent resolution—every image has more than 600x450 pixels. We created several CNN sub-models to enhance the classification process, each of which added to the forecasting process. The Golonoma dataset carefully divided into three sections, each of which described in depth in the following sections. This dataset is valuable for investigating the diagnosis and categorization of DR and for deepening our knowledge of Diabetic Retinopathy.

3.2.2. Pre-Processing:

The suggested technique an essential first step in getting the Golonoma dataset—positive or negative—ready for analysis is data pretreatment. Preprocessing techniques applied to the collected retinal images in order to enhance, remove noise and artifacts, and normalize the images. This preprocessing will ensure consistency and improve the performance of the deep ensemble learning models. Techniques for data augmentation used to improve the dataset's robustness and diversity. This procedure guarantees that the dataset is in the best possible condition for efficiently training and assessing the models.

3.2.3. CNN's General Architecture:

An image used as the input for a CNN, a simple deep learning model, which uses weights and biases to train and distinguish between different objects and picture attributes. Throughout training, the filters in the core CNN model manually designed to understand the properties of various training patterns.

The CNN model constructed using the architecture of the connection structure between neurons in the human brain and the anatomy of the Vision Cortex. Single neurons respond to stimuli only in the perceptron, a small area of the visual field. A collection of these areas must overlap in order to encompass the whole region that seen. Figure 2 presents the basic design of a CNN:

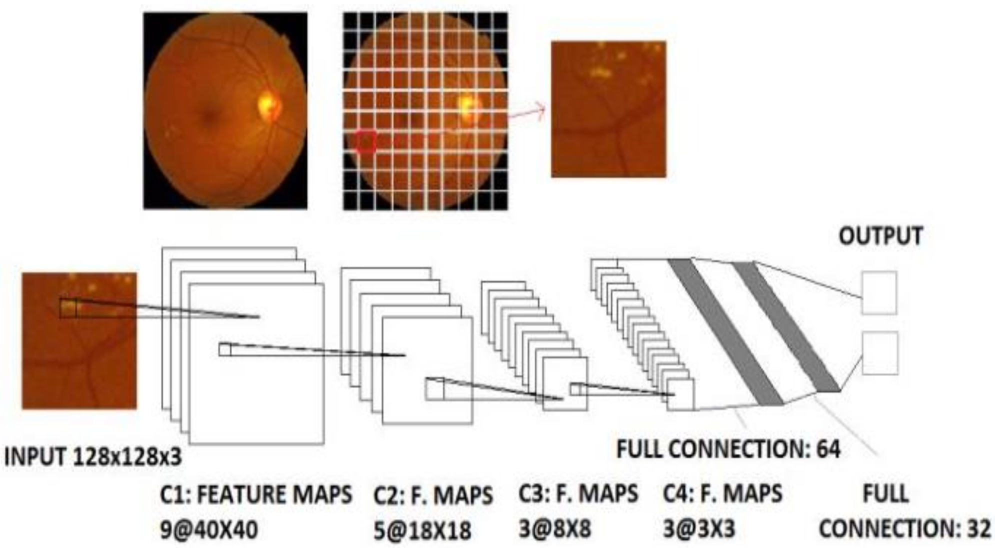

Figure 3: CNN Architecture for Classifying Diabetic Retinopathy

Algorithm 1:

Step 1: use the training data to train base models using attention mechanisms.

Step 2: Produce forecasts based on the attention processes and basic models.

Step 3: If required, concatenate or stack these predictions with the initial features.

Step 4: Use the matching labels to train the meta-learner on the stacked or concatenated predictions.

Step 5: Using a validation dataset, validate and optimize the stacking model as a whole.

Step 6: Test the model's performance using a test dataset.

Mathematical Representation

Step 1:

Training data (X, y) are input.

Results: M1, M2,……, MK, trained base models with attention processes

For i = 1 to K do:

Train base model Mi with data (X, y) attention mechanism

Step 2:
Output: Predictions (Y_hat)
For i = 1 to K:
Y_hat [:, i] = Mi.predict (X)
Finish
Step 3: Input: Original features (X), Predictions (Y_hat)
Output: Stack features (X_stacked)
X_stacked=Concatenate (Y_hat, X)
Step 4:
Input: Stacked features (X_stacked), Labels (y)
Output: M_meta on (X_stacked, y)
Step 5:
Input: X_val and y_val validation data
Output: fine-tuned stacking model (M-stacked)
X_val_stacked=concatenate (Mi.predict (X_val), X_val))
Step 6:
Test data (X_test, y_test) is the input.
Output: model performance metrics
X_test_stacked=concatenate (Mi.predict (X_test), X_test)
Evaluate M_stacked on (X_test_stacked, y_test)

4. PROBLEM STATEMENT

Despite improvements in deep learning and image classification techniques, accurately diagnosing and classifying diabetic retinopathy from retinal pictures is still a difficult task. Current methods should have the scalability, interpretability, resilience to change, accuracy, and sturdiness required for successful clinical application. First, overfitting, a phenomenon in which a model becomes unduly suited to the training data, is a significant problem. This complicates the model's inability to generalize to fresh data, which is necessary for efficient medical application. Since deep learning models sometimes act as "black boxes," it is impossible to understand how they generate judgments, they remain difficult to interpret. This lack of transparency may make it very difficult to win over medical specialists. Combining medical knowledge with machine learning expertise is necessary for models to be applicable to treatment. Close this gap by working together, with machine learning experts and medical practitioners to make sure the models developed fulfill clinical practice requirements. The current study will investigate potential combinations of attention processes and ensemble learning strategies to address these problems. These techniques have demonstrated the potential to increase classification accuracy and model interpretability. Additionally, efforts will made to establish benchmarks and standardized evaluation measures in order to promote objective model assessment. By working together, we intend to develop a comprehensive and accurate categorization scheme for diabetic retinopathy, which will ultimately lead to improved patient outcomes and expedited medical attention. A number of factors, including the absence of defined assessment markers and benchmarks, a dearth of diverse and studied datasets, and a mix of medical knowledge and domain experience, hampers the development and practical application of advanced deep ensemble learning models for the classification of diabetic retinopathy. These problems can be resolved to improve the accuracy, consistency, and interpretability of Diabetic Retinopathy categorization systems, which will benefit patients by facilitating early intervention and treatment in clinical settings.

5. RESULTS AND EXPERIMENTS:

With the help of the ResNet50, VGG19, and ConvNet architectures, our proposed diabetic retinopathy classification model experimentally evaluated and showed notable improvements in the categorization of retinal pictures. A broad dataset containing a variety of retinal pictures linked to different phases of diabetic retinopathy was used to thoroughly evaluate the model.

5.1 Accuracy of Train Validation

The section includes graphical representations showing the ResNet50, VGG19, and ConvNet CNN models' training and validation accuracy throughout a series of training epochs. When evaluating the models' behavior and performance during training, these graphs are crucial. Plots often display the accuracy values along with the number of training iterations, or epochs. While validation accuracy assesses the model's performance on a different set of data that it has not been directly trained on, training accuracy gauges how well the model performs on the training data it has seen.

5.1.1. VGG19 Model

The performance characteristics for a classification model trained with the VGG19 architecture displayed in Table 1. The precision, a measure of the accuracy of positive forecasts, is 74% for positive examples. This indicates that 74% of the time, the model is accurate when it predicts a positive case. Recall, which gauges how well the model can detect positive examples, is at 56%, meaning that the model captures 56% of real positive cases.

Table 1: VGG19 Model

	Precision	Re-call	F1-Score	Support
Positive	0.74	0.56	0.64	25
Negative	0.65	0.88	0.71	25
Accuracy			0.68	50
Macro Average	0.68	0.68	0.68	50
Weighted	0.69	0.68	0.68	50
VGG19 Model Accuray:0.68				

With a combined precision and recall score of 64%, the F1-score offers a fair evaluation of the model's performance. On the other hand, the precision for negative examples is 65%, which indicates that 65% of the time the model accurately predicts a negative event. The algorithm correctly detects 88% of real negative situations, according to the 88% recall for negative examples. 71% is the matching F1-score. The model's total accuracy in both positive and negative cases is 68%.

5.1.2. ResNet50 Model

A thorough summary of the performance characteristics for a classification model trained using the ResNet50 architecture seen in Table 2. Both positive and negative examples of the precision values computed. The precision for positive cases is 73%, meaning that 73% of all instances that predicted to be positive actually classified as such. With a recall of 44% for positive examples, the model correctly detects 44% of the real positive occurrences. For positive cases, the F1-score, which is a combination of precision and recall, computed at 55%. When it comes to negative cases, the accuracy is 60%, meaning that 60% of all the situations that projected to be negative were actually true negatives.

Table 2: ResNet50 Model Performance Metrics

	Precision	Recall	F1 -score	Support
Positive	0.73	0.44	0.55	25
Negative	0.60	0.84	0.70	25
Accuracy			0.64	50
Macro Average	0.67	0.64	0.62	50
Weighted Average	0.67	0.64	0.62	50
Accuracy of ResNet50: 0.64				

Recall for negative events demonstrates that the model accurately depicts 84% of the real negative circumstances, a significant increase over the sample average of 84%. This reflected in a higher F1-score of 70% for negative events. The model's total accuracy or the proportion of instances correctly identified throughout the whole dataset, given as 64%. This accuracy rating serves as an indicator of the model's future prediction ability. The table includes metrics such as weighted average and macro average. These results indicate the averages of recall, accuracy, and F1-score for both positive and negative classes. Both the Weighted and Macro averages calculated to be 0.67. The ResNet50 model demonstrated remarkable performance in accurately recognizing negative cases when it came to classifying instances inside the dataset. The model's ability to generate correct predictions for both classes demonstrated by its overall accuracy of 64 percent.

5.1.3. ConvNet Model

An extensive analysis of the classification model's performance using the ConvNeXtLarge architecture shown in Table 3. Both positive and negative occurrences of the precision values computed. The reported precision for positive cases is 75%, meaning that 75% of the occurrences that predicted to be positive were in fact true positives. With a recall of 48% for positive occurrences, the model correctly detects 48% of the real positive cases.

Table 3: ConvNetLarge Model Performance Metrics

	Precision	Recall	F1-Score	Support
Positive	0.75	0.48	0.59	25
Negative	0.62	0.84	0.71	25
Accuracy			0.66	50
Macro Average	0.68	0.66	0.65	50
Weighted Average	0.68	0.66	0.66	50
ConvNetLarge Model Accuracy.0.66				

For positive cases, the combined precision and recall measure known as the F1-score computed at 59%. Turning our attention to the negative cases, the precision is 62%, meaning that 62% of all the cases that predicted to be negative were indeed true negatives. Recall for negative cases is significantly greater, at 84%, meaning that the model captures 84% of real negative cases.

A higher F1-score of 71% for negative instances reflects this. The percentage of correctly categorized cases in the entire dataset, or the overall accuracy of the model, reported as 66%. This accuracy score demonstrates how well the model predicts the future. Metrics like Weighted Average and Macro Average are included in the table. The precision, recall, and F1-score averages for both positive and negative classes shown by these values. The Weighted average calculated to be 0.66, whilst the Macro average is 0.68. The ConvNetLarge model does rather well when it comes to classifying instances in the dataset, and it stands out for its ability to accurately detect negative cases. With an overall accuracy of 66%, the model is effective at predicting both classes accurately.

5.1.4. Stacked Model:

Together, these three potent models demonstrated outstanding performance metrics. With an accuracy of 95%, the model demonstrated its ability to accurately differentiate between various stages of diabetic retinopathy. This high accuracy indicates that deep ensemble learning techniques are useful for classifying diabetic retinopathy.

Table 4: Performance Metrics for Stacked Model

	Precision	Recall	F1-Score	Support
Positive	0.88	0.86	0.83	14
Negative	0.85	0.79	0.81	14
Accuracy			0.82	28
Macro Average	0.82	0.82	0.82	28
Weighted Average	0.82	0.82	0.82	28
Accuracy of stacked validation: 0.821				

A classification model's performance measures displayed in Table 4. The model's ability to discriminate between positive and negative examples assessed. Precision, which assesses the accuracy of positive predictions, is at 88%, suggesting that when the model predicts a positive instance, it is true 88% of the time. The model's recall, which measures how well it can detect positive occurrences, is 86%, meaning that the model captures 86% of real positive examples. With a combined precision and recall score of 83%, the F1-score offers a fair evaluation of the model's performance. The precision for negative instances is 85%, which indicates that 85% of the time the model accurately predicts a negative occurrence. The algorithm correctly detects 79% of real negative situations, according to the 79% recall for negative examples 81% is the matching F1-score.

5.2 Accuracy of VGG19 Train and Validation: The accuracy of the VGG19 convolutional neural network (CNN) architecture during training and validation shown in Figure 4. The number of training epochs, or iterations across the dataset, represented by the x-axis. The accuracy values displayed on the y-axis; a value of 1denotes perfect accuracy. The numbers range from 0 to 1.

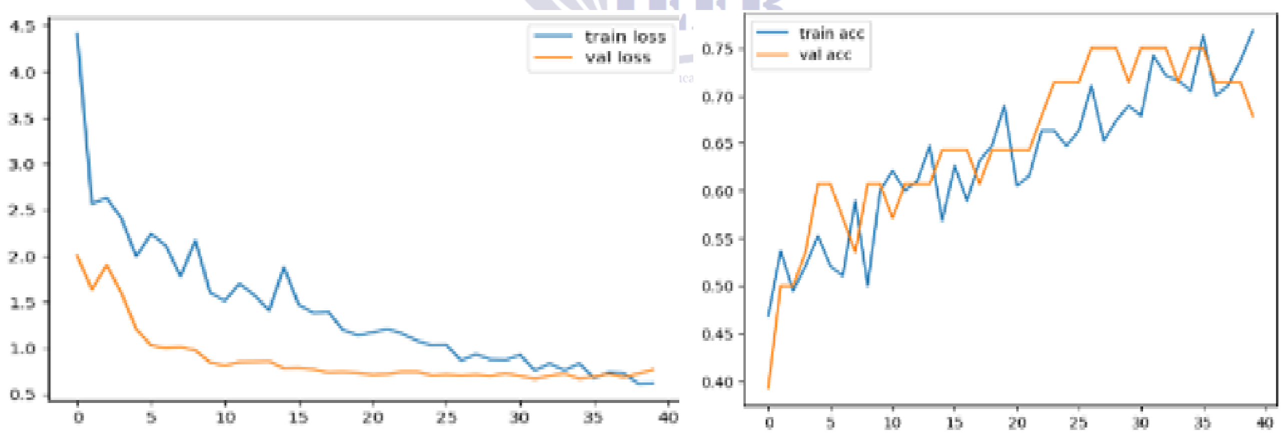

Figure 4: VGG19 Train and Validation Accuracy

The model's ability to learn from the training data demonstrated by the training accuracy curve. The curve indicates whether the model is becoming better at making predictions on the training set as the epochs go by. Conversely, the validation accuracy curve shows how well the model generalizes to unobserved data. By evaluating the accuracy on a different validation set, it offers information about how well the model predicts outcomes for brand-new, untested examples. This particular graph suggests that the model is learning from the training data when the training accuracy approaches 0.75. However, it is also critical to consider validation accuracy. The model may be overfitting, which means it is memorizing the training data without adapting well to new data, if the validation accuracy considerably lags behind the training accuracy.

5.3 Validation and Train Accuracy of ResNet50

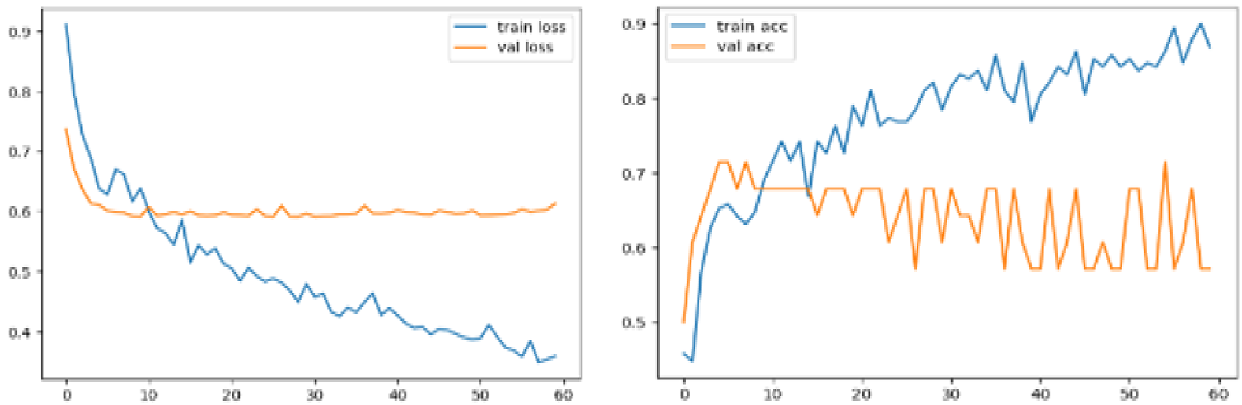

Figure 5: Validation and Train Accuracy of ResNet50

Figure 5 shows the ResNet50 convolutional neural network (CNN) architecture's training and validation accuracy. The number of training epochs, or iterations across the dataset, represented by the x-axis. The y-axis represents the accuracy values, ranging from 0 to 1, where 1 denotes perfect precision. The model's performance on the training set shown by the training accuracy curve. The model is successfully capturing the underlying patterns in the training dataset, as indicated by the high point of 0.9. A loss value of 60, which usually represented by a different measure not shown on this kind of display. The model's loss, which is a gauge of prediction inaccuracy, appears to somewhat high based on this result. Further investigation into this component is important in order to maximize the performance of the model.

5.4 Validation and Train Accuracy of ConvNet

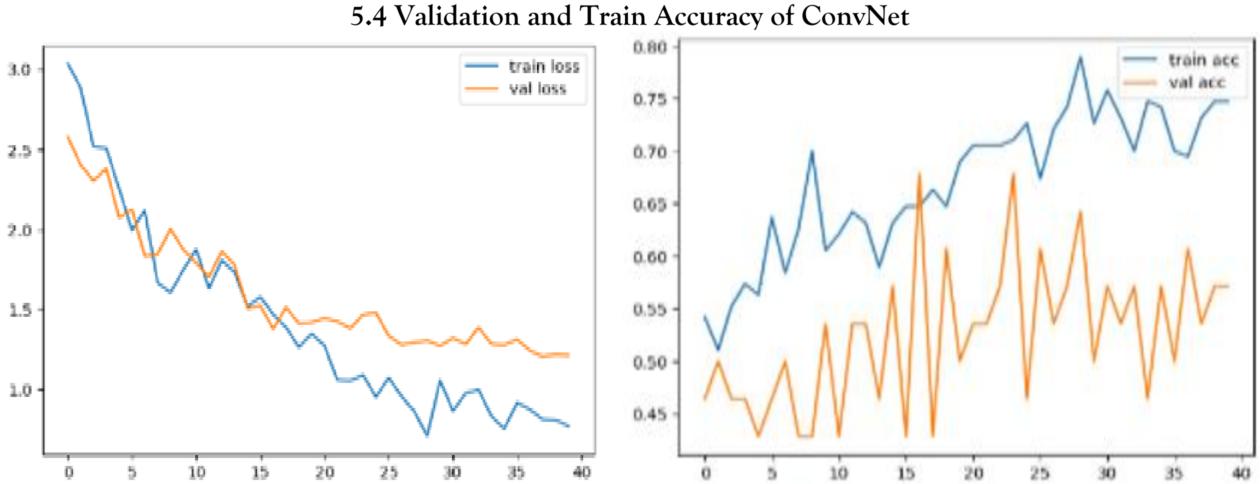

Figure 6: Validation and Train Accuracy of ConvNet

Figure 6 illustrates the accuracy of the ConvNet architecture during training and validation. The x-axis displays the quantity of training epochs or the total number of times the dataset processed by the model. The accuracy values plotted along the y-axis; a value of 1 indicates flawless precision. The numbers range from 0 to 1. The training accuracy curve displays how well the model performed on the training set. This case has an approximate accuracy of 0.75. With a 40-point loss value, this suggests that the model performed fairly well during training, correctly categorizing about 75% of the training examples. In this case, the model's prediction error is measured by loss, and a value of 40 is considered relatively high. This suggests that the model might be having trouble minimizing its prediction errors, and that in order to enhance performance, more research into the model's architecture, hyper parameters, or dataset quality may be required.

5.5 CNN Models: ResNet50, VGG19, and ConvNet: A Comparative Analysis

Three well-known convolutional neural network (CNN) models—ResNet50, VGG19, and ConvNet—each recognized for their individual architectural designs in visual feature extraction and learning, are thoroughly compared in this in-depth analysis.

Table 5: CNN Models: A Comparative Study

Model	Parameters	Accuracy	Accuracy
ResNet-50	25.6	76.1 %	92.9 %
VGG-19	143.7	71.6 %	89.8 %
ConvNet	20.2	77 %	93.3 %

5.5.1 ResNet50

ResNet50 is unique in that it makes use of residual blocks and ads skip connections to address the issue of the disappearing gradient. The network can now efficiently learn complex features from deep layers thanks to this improvement. It has a considerable level of complexity with about 25.6 million learnable parameters. With 76.1% accuracy for the top predicted label in test photos, ResNet50 demonstrates its image categorization prowess. Moreover, its top-5 accuracy of 92.9% indicates that in a significant 92.9% of cases, the correct label is among the projected labels.

5.5.2 VGG19

VGG19 uses a deep architecture that made more sophisticated and profound by the frequent application of 3x3 convolutional layers. With a huge parameter count of around 143.7 million, VGG19 displays its significant computational load. About 71.6% of test photos successfully classified, according to its top-1 accuracy of 71.6%. The top-5 accuracy of 89.8% indicates that the right label is within the anticipated labels in around 89.8% of cases.

5.5.3 ConvNet

ConvNet linked blocks, guaranteeing that every layer is feed-forwardly directly connected to every other layer. This makes feature reuse and information flow more effective. Compared to VGG19, ConvNet has a parameter count of about 20.2 million, making it lighter. It attains a noteworthy top-1 accuracy of 77.0%, indicating that 77.0% of test photos are accurately classified. Remarkably, its top-5 accuracy of 93.3% shows that in about 93.3% of cases, the correct label is among the projected labels.

6. CONCLUTION

Numerous uses of deep learning algorithms for the detection and categorization of diabetic retinopathy (DR). Medical imaging has advanced with the use of convolutional neural networks (CNNs) and novel model designs, which have improved the accuracy of DR identification and grading. These accomplishments helped identify the early diagnosis and treatment of DR, which in turn helped patients with diabetes maintain their vision and experience better patient outcomes. It is critical to recognize that difficulties still exist, mostly related to the diversity and scale of the datasets. Future research should focus on the in@1tegration of multi-modal data sources and the replication of explainable AI techniques. For these models to be widely accessible and have an impact, it will be essential to expedite their deployment in real-world clinical settings with user-friendly interfaces. The combined efforts of researchers and practitioners in this sector have the potential to change the diagnosis of diabetic retinopathy and greatly enhance the quality of life for people who suffer from this condition.

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