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Article

Hybrid Deep Learning Ensemble Model Using ResNet50, VGG16, and MobileNetV2 for Eye Disease Identification

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Abstract: —Diabetic eye illnesses, including retinopathy due to diabetes and macular edema, have been a category of ocular disorders that may impact individuals. Timely identification is essential for preventing blindness and vision impairment; nevertheless, physical diagnosis is labor-intensive and requires specialized expertise. This paper introduces "Hybrid Deep Diabetic," an ensemble combination of models deep learning techniques system for the automatic diagnosis of eye illness. This system combinesEyeNet, ResNet50, VGG16, &MobileNetV2 to hybrid models that enhance classification accuracy. EyeNet used as a bespokeDeep Learning Technique convolutional neural network (CNN) optimized in retinal imagegeneration , while models that have been trained (ResNet50, VGG16, MobileNetV2) use transfer learning to extract robust features.The hybrid model integrates predictions using an ensemble methodology, enhancing diagnostic accuracy compared to singular models. The Calculate metrics: accuracy,recall, precision, &F1-score—indicate that combined approach surpasses both solo CNNs and conventional machine learning methods. The methodelevated categorization precision, facilitating prompt identification anddiminishing reliance on human screening. Future improvements may include real-time use in clinical settings and interaction with telemedicine systems for broader accessibility.
Keywords: —Diabetic retinopathy, deep learning, hybrid CNN, ensemble learning, EyeNet, ResNet50, VGG16, MobileNetV2,diabetic eye disease detection.

1. INTRODUCTION

Diabetic Eyes Disease, a significant complication of diabetes, is among the primary causes of vision harm and blindness globally. It encompasses a range of illnesses including Diabetic Retinopathy[1] (DR), Diabetic Macular Edema (DME), as well as more eye conditions caused by elevated blood glucose levels. The International Diabetes Federation (IDF) projects that the worldwide diabetic population will Outdo 700 million by2045, raising the chance of diabetes-related visual harms.Timely identification and precise diagnosisof diabetic conditions are essential to avoid visual impairment. Traditional diagnosis, however, mostly depends on the manual evaluation of retinal fundus images by eye specialists [2], which is both time-consuming and resource-intensive. To address these constraints, automated diagnostic systems using Artificial Intelligence (AI)Techniques [6], especially Deep Learning (DL) Algorithms [5], have developed as potential alternatives in the past years.

Deep Technique-Convolutional Neural Networks (CNNs) [21] has shown exceptional efficacy in analysing retinal fundus images[14] for the identification of diabetic eye disease characteristics, including tiny blood vessels, hemorrhages, and exudates. No deep learning system has shown universal superiority across various tasks and datasets, mostly because to variations in data properties, clarity, and noise levels. A combination or ensemble strategy is essential to overcome this constraint.The suggested CNN Deep Diabetes [22] system presents a combined multi-model deep framework for the automatic diagnosis of eye illness. This system combinesEyeNet, ResNet50, VGG16, &MobileNetV2 into hybrid model to classification accuracy. The performance each algorithm is based on accuracy, precision, recall, & FCSORE. Hybrid Deep Diabetes is a multimodal system that achieves an accuracy rating of 94.26%.

The system enhances Model performance[23] by introducing a Hybrid Learning Ensemble System that combines the advantages in EyeNet, ResNet, VGG, &MobileNetV2 into a unified architecture. Eachmodel has distinct feature extraction capabilities: EyeNet offers lightweight feature learning unique to the retina, ResNet delivers deep residual representation for intricate lesion identification, VGG provides stable hierarchy pattern mapping, and MobileNetV2 introduces enhanced accuracy-to-parameter efficiency via compound scaling.By integrating these models into an ensemble method, the hybrid architecture effectively captures all low-level and advanced retinal patterns, hence enhancing resilience to analysis of images, noise, and varying stages of disease severity. This multi-model fusion gain superior generalization and diagnostic accuracy relative to individual networks, enablingdependable early identification of diabetic ocular conditions including DR, DME, cataract, & glaucoma.

2. RELATED WORK

Zhang proposed a paradigm for the active detection of the presence& severity of diabetic retinopathy (DR)[1]. By utilizing multiple Deep learning architectures: ResNet50 as well as InceptionV3, DenseNets, Xception, and InceptionResNetV2. Althoughsuggested technique achieved a score of 97.5% & an accuracy 97.7%, the modelsrequire evaluation with a more comprehensive and thorough dataset.

Samanta developed a CNN-based [22] TL architecture with colour fundus images, which performs well in classification of diabetic retinopathy (No DR, Mild DR, Strong DR, & Proliferative DR) based on solid exudates, blood vessels, & texture within a constrained data. They used this model across a number of platforms, such Inceptionv1, Inceptionv2, Inceptionv3, Xception, VGG16, ResNet-50, DenseNet, andAlexNet.

Wang, provide a comprehensive analysis on use of deep system to detection diabetic retinopathy along with other ocular disorders. This study examines ophthalmology-specific use cases for(CNN) convolutional neural networks [21]&(RNN) Recurrent neural networks , along withdifferent deep learning architectures. This paper examines capability of deep learning techniques toimprove the accuracy & efficiency in illness diseases.

A. M. A & S. S. S. Priya suggested a deep technique neural network using trained (CNN) Convolutional Neural Network [22] VGG-16 &MobileNet-V2 to recognize different kinds of diabetic retinopathy (DR). This research examines if algorithms for deep learning & image generation methods may use to detect & categorize diabetic retinopathy.

Srinivasan, examine the application of cellular automata as well as deep technique for detection of diabetic retinopathy [13]. These study offers a method for assessing retinal images and identifying indications in diabetic retinopathy via the use of convolutional neural network with cellular automata models. The paper highlights the efficacy of this hybrid method in effectively identifying and categorizing the disease.

Gargeya, Deep neural networks have been proposed as a component of an automatic methodto identifying diabetic retinopathy. This article discusses the use of CNNs [21] to analyse retinal fundus images and identify signs of diabetic retinopathy. The study demonstrates the potential of advanced learning algorithms to accurately and effectively diagnose diabetic retinopathy.

N. V. R. G, M. Ch, R. Ch, & A. B introduced an innovative deep-learning technique [13], Mobile NetV2, which emphasizes both precise diagnosis and privacy safeguarding. The used model integrates several conv2d layer & activation function to accurate predict &categorization in diabetic retinopathy phases. Secure Hash Algorithm (SHA-512) generates distinct hash value for DRfigureto provide security. This modelreduces likelihoodin eyesight issues.

L. Qiao suggested a technique using convolutional neural networks (CNN) to identify microaneurysms in fundus images [22]. This technique incorporates deep technique is fundamental element to the partition of pictures with low-delay inference. The semantic division approach is used classify fundus figures as DR & NDR. This approach classifies images according to shared semantics to pull out microaneurysm features.

This paper "Deep Ensemble Learning for Diabetes Retinopathy Screening [10]" by T. Vo, D. Truong, and P. Nguyen, published in 2021, introduces an ensemble of neural networks with deep learning, namely DenseNet and InceptionV4, for the purpose of screening diabetic retinopathy. Each model was trained autonomously, and their results were consolidated using weighted voting. The ensemble surpassed individual models in sensitivity as well as specificity, especially on unbalanced datasets.

Bellemo, reassess the recent data of diabetic retinopathy via artificial intelligence (AI) [6]. This study discusses the automatic examination of retinal images with AI techniques, including deep techniques. This study points up practical applications that AI has in diabetic retinopathy, during accentuating it capacity to enhance accessibility &efficiency within healthsector environments.

The study "Multi-Scale Deep Learning in Retinal Illness Classification" by K. Zhang, L. Wang, and J. Huang, published in 2022, investigates multi-scale convolutional neural networks (CNNs) that evaluate retinal images [18]across various resolutions. The approach adeptly identifies both small and large lesions in fundus images by integrating characteristics from tiny and large receptive fields. The findings indicated enhanced rates of detection for early-stage diabetic retinopathy & diabetic macular edema.

M. Rahman, T. Chowdhury, and A. Habib (2022) developed a lightweight CNN tailored for mobile deployments to facilitate diabetic retinal disease screening [9] in resource-limited environments. Notwithstanding the decreased complexity, the model attained an accuracy over 85% on the Messidor&IDRiD datasets. The document emphasizes the significance of resource-efficient artificial intelligence for remote healthcare provision.

3. DATASET DETAILS

The collection comprises retinal fundus pictures classified into many categories, including healthy retinas & different phases of diabetic eye disease. The dataset categorizes the data into four distinct types of diseases or conditions. Our analysis included solely standard fundus and cataract imaging. The study has a total of 1,376 photos. Diagnostic keywords from surgeons accompany the photos and provide valuable insights for clinical evaluation. The dataset includesphotos eyeillness, including cataract, diabetic retinopathy (DR), diabetic macular edema (DME), & glaucoma. All these photos are modified to enhance dataset size then trained using algorithms.

A comprehensive preprocessing pipeline was established for fundus images obtained from many camera sources like Kowa, Zeiss, & Canon, prior to model development to standardized the input data and to improve model performance.

This section delineates four distinct CNN models that are used (EyeNet, ResNet-50, VGG-16, &MobileNetV2) for cataract detection in fundus images, along with their respective topologies. EyeNet offers light retinal-specific feature learning for lightweight architecture, mobile, including embedded apps. ResNet-50 is adept at training extensive networks and acquiring high-level insights from intricate medical images. VGG is a more profound variety of VGG, characterized by a straightforward, homogeneous architecture using modest convolutional filters to capture nuanced visual information. MobileNetV2 can simultaneously learn multi-scale features using various filter sizes, which is advantageous for identifying cataract images. We choose each model to tackle the issues associated with medical image classification and provide diverse methodologies for cataract detection.

The phrase "ensembles of models" denotes the integration of outcomes from several statistical models in a unified forecast. This approach enables the model's capabilities to more accurately represent enhanced estimates and attain superior performance compared to any individual model. This paper presents a CNN architecture using three established pretrained models: VGG-16 (Simonyan and Zisserman, 2014), ResNet50 (He et al., 2016), &MobileNetV2, which serve as feature extractors.

4. PROPOSED METHODOLOGY

The proposed system introduces the Hybrid Learning Ensemble System that integrates the benefits of EyeNet, ResNet, VGG, and MobileNetV2 into a cohesive architecture. Each model has unique feature extraction capabilities: EyeNet enables straightforward retina-specific feature training, ResNet generates profound residual visualizations for complex lesion identification, VGG ensures resilient hierarchicalextraction of features, and MobileNetV2achieves remarkable accuracy-to-parameter efficiency through compound scaling. The hybrid approach improves resistance to image variability, noise, and disease severity stages by merging these models together using a weighted ensemble method, successfully capturing low-level & high-level retinal figures. This multi-model fusion achieves enhanced generalization and diagnostic precision compared to individual networks, allowing reliable early detection of diabetic eye illness such as diabetic retinopathy, diabetic macular edema, cataract, & glaucoma.

Hybrid CNN is tailored for retinal image processing, while model that have being learned (ResNet50, VGG16, MobileNetV2) employ transfer learning to generate robust features. Convolutional Neural Networks (CNNs) Usually used to train deep learning algorithms on medical imagery. This happens because CNN continually extracts attributes while analyzing incoming photos. In ocular pathology photography, spatial connections are essential in retinal photos, especially regarding blood vessel loss and the buildup of yellow water in the retinal area.

A CNN consists of many types of layers. Layers are implemented for the extraction of features and patterns. Convolutional neural network (CNN) comprises Convolutional, Pooling, and Fully Connected layers. The convolutional layer extracts characteristics like edges and textures using filters, while the pooling layer reduces dimensionality, retaining critical information and eliminating extra components. The fully connected layers then amalgamate this data to provide the last prediction.

VGG16 is a convolutional neural network (CNN)technique with 16 layers, consisting of 13 convolutional layers with 3 fully connected layer. ResNet50 has 50 layers used for image categorization and computer vision applications. MobileNetV2 is a compact but potent model that achieves excellent accuracy in picture classification comparedtoothermodels.

Key performance metrics used to evaluate models encompass recall, accuracy, precision, F1-score, and confusion matrix. To monitor model stability, detect instances of overfitting, and tune hyperparameters, one may examine both training &validation accuracy rating /loss graphs.

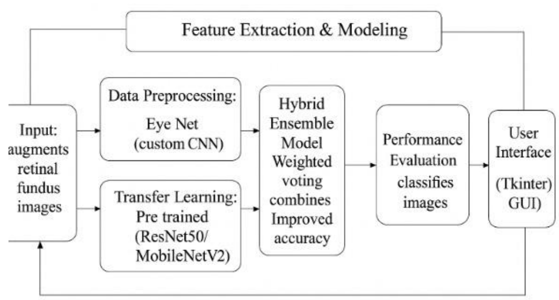

Figure 1:Framework for Suggested Model's System

Figure [1] illustrates the structure of the system's design. Utilize the retinal fundus photos as input, thereafter preprocess the images by resizing and normalization. Eyenet is used for extracting characteristics from photos. ResNet50, VGG16, and MobileNetV2 are used pre-trained model for robust attribute extraction. The hybrid ensemble model integrates all forecasts to enhance accuracy. Performance Calculation computesmetrics: accuracy, precision, recall, &F1-score.Predict the occurrence in diabetic eye illness based on input photographs.

5. RESULT AND DISCUSSION

This work presents deep learning techniques for the identification in diabetic eye illness, namely VGG16, ResNet50, and MobileNetV2. These models are employed to categorize the prevalent diabetic ocular conditions: Diabetic Retinopathy (DR), Diabetic Macular Edema (DME), Cataract, & Glaucoma. The proposed models were assessed according to each one's accuracy, recall, precision, &F1-score. These findingsshow hybrid deep learning algorithms achieve an accuracy of 94.26%.

The figure in Figure [2] illustrates the matrix of confusion for an automated learning model that integrates EyeNet, ResNet50, VGG16, &MobileNetV2 architectures. A confusion matrix evaluates the efficacy of a model for classification. Row denote real "True class" labels, whereas the columns signify the anticipated labels. The diagonal cells indicate the quantity of accurate forecasts for each class. The model accurately predicted 1747 occurrences of the "Normal" class & 1118 cases of the "ODC" class. The off-diagonal cells indicate the erroneous predictions. Specifically, there were 1624 occurrences of the "DR" category misclassified as "DR" and 42 occurrences of the "DR" category misclassified as "Normal". The concept seems to pertain to the categorization of retinal illnesses, since the categories "DR" (Diabetic Retinopathy), "MH Normal" (Macular Hole Normal), & "ODC" (Optic Disc Cupping) are often used in such research.

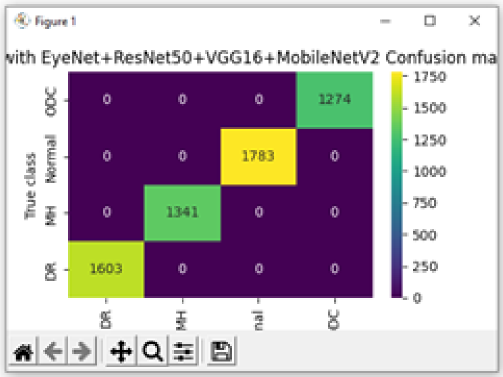

Figure 2: The Hybrid Deep Diabetic of Confusion matrix

Figure [3] illustrates a performance graph for each approaches in Hybrid Deep Diabetes. The graph illustrates the performance of several algorithms along the x-axis. The y-axis denotes the performance score, spanning from 0 to 100. The performance measures (Accuracy, F-Score, Precision, & Recall) are shown by distinct colored bars for each method.

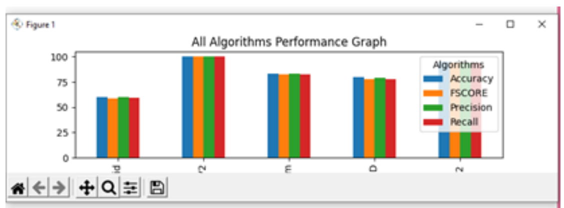

Figure 3: All Algorithm Performance Graph of Hybrid Deep Diabetic

Comparative Performance Summary

The table [1] presents the metric values along with Accuracy, Precision, Recall, &F1-Score, for all hybrid models. Each model exhibits distinct values. The hybrid models provide more accuracy than the other types. Hybrid Deep Diabetes is a multimodal system that achieves an accuracy rating of 94%.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
EyeNet SGD	79.40	79.57	77.74	77.96
EyeNet Adam	83.53	83.12	82.70	82.53
MobileNetV2	78.83	78.32	78.25	78.26
Adam&Valid Padding	94.48	94.31	94.13	94.16
EyeNet+ResNet50+VGG16+MobileNetV2	98.57	98.57	98.57	98.57

Table 1: Model Performance Metrics

6. DISCUSSION

This work presents deep techniques models used as identification of eye illness, namely ResNet50, VGG16, and MobileNetV2. The above models are used to categorize the prevalent diabetic ocular conditions: Diabetic Retinopathy (DR), Diabetic Macular Edema (DME), Cataract,& Glaucoma. These proposed models were assessed according to each one's accuracy, recall, precision, &F1-Score.The findings indicate that the models developed using deep learning had highest classification exactness rating of94.26%. This experiment utilizes a dataset of several images. The initial count of photos prior to enhancement is 1,376. The total number of photos after enhancement is 30,001. The total photos are categorized into three classifications:1. Training images: 19,200; 2. Validation images:

4,800; 3. Testing images: 6,001. Simultaneously, the MobileNetV2& VGG16 models achieved optimal values in the evaluation metrics for the non-augmented data.

Our deep learning methods outperformed the accuracy of prior experiments. Consequently, we advocate for the use of the MobileNetV2 model, derived from fundus images, in detecting the health status of people with diabetes regarding DR, DME, cataract, including glaucoma. We have implemented many deep techniques withoutcomes,along with intention that they may serve as a foundation for developing a system capable of diagnosing eye illnesses using fundus images.

7. CONCLUSION

This study included the building and evaluation of a multiple-classification deep learning model, termed the Deep Diabetic framework, for the detection of Diabetic Retinopathy (DR), Diabetic Macular Edema (DME), Glaucoma, &Cataract from fundus images. Accurate early diagnosis of these disorders is essential for establishing appropriate therapy. Still, identifying eye diseases using fundus imaging is tricky, and even highly skilled ophthalmologists are exposed to misdiagnosis. Three pre-trained convolutional neural network models are used for comparing and evaluating the proposed convolutional neural network technique. Evaluated diabetic retinopathy dataset's performance using precision, recall, F1-score, specificity, & accuracy.

These investigation in several CNN architectures, including VGG16, ResNet, the Inception models, has shown their performance in extracting patterns from retinal images for precise diabetic retinopathy identification. To further enhance diagnosis, data augmentation methodologies and models are being developed to increase the performance the generalizability of novel end-to-end learnable deep learning models.

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