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A Multi-Kernel Sparse Dense Network (MKSDnet) For Retinal Disease Risk Classification

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Abstract: *The prevalence of eye diseases and the associated loss of vision have raised considerable concerns about global public health. Early detection and management are crucial to prevent permanent impairment and improve the chances of recovery for those affected. One way to discover eye diseases early is to use Machine Learning and Deep Learning algorithms to identify them. To do this, there are variety of pre-trained models available, such as VGG19, Xception ,MKSDnet and ResNet18. In this project, we suggested a model which comprises DenseNet modules and multi-kernel learning approach for classifying retinal fundus images automatically to determine the risk of vision loss. It uses retinal fundus images gathered from various populations. Images from various eye ailments, such as routine vision, Diabetic Retinopathy (DR), Age-Related Macular Degeneration (ARMD), and glaucoma, are included in the dataset. We have used about 860 retinal fundus images from the newly introduced Retinal Fundus Multi-Disease Image Dataset 2.0 (RFMiD2.0), respectively. Around 50 diseases are identified in RFMiD 2.0 Datasets. Early detection of those at risk for vision loss may facilitate prompt intervention, Improving treatment outcomes and lowering medical expenses. Additionally, automated classification techniques can aid healthcare professionals in efficiently evaluating many patients, facilitating the best resource allocation and treatment.*

Keywords: Deep learning, Retinal fundus images, Binary classification, Eye disease, Neural network.

I. INTRODUCTION

The "A Multi-Kernel Sparse Dense Network for Retinal Disease risk classification" initiative tackles a serious worldwide health concern: eye conditions that can cause blindness or visual impairment. Early and precise identification of illnesses including Age-Related Macular Degeneration (ARMD), Diabetic Retinopathy (DR), glaucoma, and other eye disorders is crucial because there are an estimated 596 million people with far vision impairment globally, including 43 million who are blind.To help with this endeavor, the research uses cutting-edge machine learning (ML) and deep learning (DL) techniques to create a model for categorizing retinal fundus photos in order to identify eye disease risks. One of the main methods used in ophthalmology to take pictures of the retina and identify different eye disorders is retinal fundus imaging. According to the report, retinal imaging has been used for diagnosis since the 1800s. Fundus imaging has become crucial in contemporary ophthalmological examinations because to technology improvements. Through the processing and analysis of fundus pictures, machine learning techniques—such as deep learning-based convolutional neural networks (CNNs)—have greatly increased the possibility for diagnosis.These methods have been improved by researchers like Zhenwei Li using methods like Grad-CAM, which increases model accuracy by highlighting important regions in an image for prediction. The research makes use of DenseNet, a kind of neural network that links every layer to every layer that comes after it, enabling more accurate and efficient learning. To extract more characteristics from the retinal pictures, the model design employs dilated convolutions and numerous kernels. The goal of the approach is to distinguish between "healthy" and "unhealthy" images in order to support early intervention to stop vision loss. To improve the model's capacity to identify minute variations across distinct retinal disorders, the researchers trained it using the Retinal Fundus Multi-Disease Image Dataset 2.0 (RFMiD2.0), which included 860 photos of different eye diseases.To maximize the quality of input photos for machine learning, the study's model goes through a thorough pre-processing step that includes

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resizing, normalization, grayscale conversion, and noise reduction. Important elements of the CNN model utilized in this investigation include deep learning ideas including activation functions, pooling, and dropout layers. Pooling allows for more efficient processing by reducing the spatial dimensions of feature maps. In order to encourage feature sparsity and concentrate on pertinent patterns while eliminating superfluous information, the DenseNet architecture used additionally incorporates "Penalized Activation Units" (PAUs). Together, these elements enable a more resource-efficient model that functions effectively even with little data. The study evaluates the MKSDnet model's efficacy by contrasting its performance with that of various CNN designs, such as VGG-19, Xception, MKSDnet, and ResNet18.With an accuracy of 99%, the suggested model produced excellent results, highlighting its potential for very accurate retinal fundus picture classification. The resilience of this model was assessed using binary cross-entropy and Kullback-Leibler (KL) divergence as two loss functions. Its high accuracy and area under the curve (AUC) value ultimately validated its strong diagnostic capacity. By letting users contribute photographs and get real-time categorization results, the model's implementation via the web application framework Streamlit makes practical usage possible. Because of its accessibility, medical professionals can utilize the model as a screening tool to maximize patient triage and guarantee efficient resource allocation.To sum up, this effort shows how machine learning may be used to improve the detection of eye diseases by classifying retinal fundus images. The great accuracy of the MKSDnet model makes it a useful tool for early detection, which is crucial for stopping the progression of many eye disorders that can cause blindness. Future research on this model might expand its applicability to multi-disease classification, giving clinicians even more thorough support. This development promises better patient outcomes and lower healthcare costs related to treating advanced-stage eye illnesses, which is in line with global health goals to combat vision impairment.

Problem Statement

Preventing vision loss and blindness requires early and precise identification of retinal conditions such glaucoma, age-related macular degeneration (ARMD), and diabetic retinopathy (DR). Nevertheless, conventional diagnostic techniques are laborious, necessitate professional interpretation, and are not scalable for widespread screening, particularly in areas with restricted access to ophthalmological services. Additionally, current deep learning models frequently have trouble generalizing to a variety of retinal imaging data, especially when the datasets are small or unbalanced.Building a Multi-Kernel Sparse Dense Network (MKSDnet) that automatically categorizes retinal fundus images as "healthy" or "at-risk" using a strong deep learning framework is the project's attempt to address these issues. The model is intended to extract a variety of fine-grained properties from retinal images by fusing the DenseNet architecture with multi-kernel learning and dilated convolutions. Enhancing classification accuracy, facilitating extensive screening, and offering a user-friendly, AI-powered diagnostic tool that promotes early detection and efficient use of resources in clinical settings are the objectives.

Objectives

1) Create a Retinal Disease Classification Model That Is Accurate: To categorize retinal fundus images, develop a deep learning-based model utilizing the Multi-Kernel Sparse Dense Network (MKSDnet) architecture. Diabetic Retinopathy (DR), Age-Related Macular Degeneration (ARMD), and glaucoma are the main causes of vision impairment and blindness, and the model should correctly identify these conditions.

2) Enhance Early Retinal Disease Detection: Create a model that can automatically classify patients and identify high-risk individuals early. Early identification lowers the risk of vision loss in afflicted patients and is essential for prompt medical care.

3) Improve Feature Extraction with Multi-Kernel Learning: To extract a variety of features from retinal fundus images, use a multi-kernel learning technique. Using sophisticated feature extraction methods, the objective is to outperform more conventional models such as VGG19, ResNet, and Xception.

4) Support Large-Scale Screening Programs: Create a model that can effectively handle huge datasets, which will enable it to be applied to extensive public health screening initiatives. In order to help in screening big populations, this goal involves making sure the model is scalable and capable of handling substantial volumes of data.

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5) Offer an Affordable and Easily Accessible Diagnostic Tool: Create an AI-powered solution that can be implemented in places where access to qualified medical personnel is scarce. Healthcare professionals should be able to triage patients and identify those who are at high risk of vision loss with the help of this user-friendly and affordable approach.

6) Support AI Research in Medical Imaging: Examine and illustrate the possibilities of integrating multikernel learning with DenseNet modules for medical picture categorization. By raising the bar for next AI-based medical diagnostic tools and increasing diagnostic accuracy, the project seeks to advance the area of artificial intelligence in healthcare.

II. LITERATURE SURVEY

[1] "Global blindness and visual impairment caused by macular diseases: a systematic review and meta-analysis," by J. B. Jonas et al. DOI: 10.1016/j.ajo.2014.06.012; American Journal of Ophthalmology, vol. 158, no. 4, pp. 808–815, October 2014.

With a primary focus on age-related macular degeneration (ARMD) and other macular illnesses, his research provides a review and meta-analysis of the most prevalent vision impairment and blindness caused by retinal diseases globally. According to studies, macular disease, which primarily affects the elderly, is the primary cause of blindness and visual loss globally. The majority of blindness is caused exclusively by ARMD, particularly in affluent areas where life expectancy is higher. He went on to say that early detection and prevention techniques are crucial because macular disease-related visual loss is frequently permanent. According to studies, as the world's population ages, more people will be afflicted by macular illnesses, particularly ARMD. in reaction to the rise in eye conditions. In order to avoid serious vision loss, it highlights the necessity of routine eye exams and early management, such as anti-VEGF medication for ARMD. The article's conclusion suggests that in order to improve prevention and treatment methods, future study should concentrate on comprehending the risk factors for macular illness, including genetic and environmental reasons.

[2] "Retinal imaging in the twenty-first century: state of the art and future directions," by P. A. Keane and S. R. Sadda, Ophthalmology, vol. 121, no. 12, pp. 2489–2500, 2014.

This article examines technological developments and talks about potential future paths for the field. The development of retinal imaging from conventional photography to technologies like fundus autofluorescence, adaptive optics, and optical coherence tomography (OCT) is thoroughly reviewed. The authors think that by enhancing the capacity to identify and track retinal disorders, these technologies enhance patient outcomes. diagram of a cross section. The research also explores how optical manipulation might make it possible to image the retina at the cellular level, offering hitherto unheard-of insight into eye disorders. With the capacity to modify pain diagnosis and anticipate infection, the incorporation of artificial intelligence (AI) and machine learning into optical imaging is seen as a crucial component of the future path. the significance of improving knowledge about retinal disorders. They also discussed issues including cost, accessibility, and the requirement for specialized training that are associated with the use of this technology in healthcare. In order to enable advanced testing to be used globally, the paper's conclusion suggests that future research concentrate on creating portable electronic devices and incorporating AI into functional graphics.

[3] "A Multi-Label Detection Deep Learning Model with Attention-Guided Image Enhancement for Retinal Images," by Z. Li, M. Xu, X. Yang, Y. Han, and J. Wang, Micromachines, vol. 14, no. 3, p. 705, 2023.
A deep learning algorithm for identifying different eye conditions from fundus photos is presented in this study. The model uses deep learning techniques to identify anomalies and incorporates sophisticated picture tracking to make it easier to identify significant elements in retinal images. By tackling two primary issues—the intricacy of retinal images and the requirement to distinguish several diseases from an image—the authors aim to increase the precision of visual disease categorization. (CNN) offers a way to concentrate on the pertinent area of the picture. The model becomes more effective and improves the distribution overall by using picture tracking to pinpoint the regions with the highest illness. The model outperformed CNN models in terms of accuracy and precision after being trained on a big dataset of retinal pictures. It is not always true that certain diseases are less prevalent than others. A prevalent issue in medicine is that some diseases might not be adequately represented in the training data, which results in subpar analysis of this pain

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line. Rare diseases are prioritized by the model using weighting, which improves their detection accuracy. They recommended that future research concentrate on enhancing the model's generalizability for various medical imaging modalities and investigate the application of additional deep learning techniques (such model generation) to enhance retinal image quality.

[4] Biomedical Signal Processing and Control, vol. 66, p. 102329, 2021; N. Gour and P. Khanna, "Multi-class multi-label ophthalmological disease detection using transfer learning-based convolutional neural network."

In order to identify ocular disorders, the study presents a multi-class, multi-label convolutional neural network (CNN) model that employs transfer learning. By employing pre-trained and optimized models for the particular purpose of identifying different eye illnesses from fundus images, the authors hope to increase the classification accuracy of retinal images. This paper's primary objective is to provide a transfer learning-based approach that can address multi-class, multi-label problems in which each image may represent several illness kinds. Retinal image data was used by renowned professionals to prelearn CNN architectures like VGG16 and ResNet50 and refine them. Transfer learning enables the model to apply features acquired from earlier learning models on massive picture networks, like ImageNet, to the goal of brain disease classification. In order to allow the model to detect numerous diseases at once, the scientists additionally include a loss function with multiple labels in each image. This significantly raises the model's detection efficiency. With excellent accuracy, this model can identify a wide range of conditions, such as macular degeneration, glaucoma, and diabetic retinopathy. The authors also stress how crucial it is to use force mechanisms, generative modeling, and data augmentation techniques like translation and rotation to enhance model detail and multi-group and multimap classification model performance. The authors also stress the significance of developing AI models that can offer insights into the model's prediction process and the requirement for bigger and more varied information to inform these models.

[5] "Multi-Label Classification of Fundus Images With EfficientNet," IEEE Access, vol. 8, pp. 212499–212508, 2020, J. Wang, L. Yang, Z. Huo, W. He, and J. Luo.

In order to identify a few retinal disorders, this work provides a version of the multi-label category of fundus images that is mostly based on EfficientNet. The authors contend that current CNN styles for the category of retinal diseases are either too computationally expensive or do not achieve the required level of accuracy, particularly when handling numerous labels in an unmarried image. In order to address this, the authors use an EfficientNet architecture, which uses more systematic scaling of the community intensity, width, and backbone than traditional CNN architectures to balance model accuracy with computing performance. The multilabel class problem, in which an unmarried photograph can be linked to several conditions, such as diabetic retinopathy, glaucoma, and age-associated macular degeneration (ARMD), is specifically addressed by the EfficientNet-based method, which is proficient on a sizable dataset of retinal fundus images. To increase the robustness of the version, the authors also employ records augmentation techniques including flipping, translation, and rotation. The use of switch learning, in which the EfficientNet model pre-trained on a sizable dataset (including ImageNet) is fine-tuned at the retinal picture dataset, is one of this paper's main contributions. This enables the model to utilize the general capabilities found during pre-education while also customizing them for the specific job of detecting retinal diseases. Metrics like accuracy, AUC (area beneath the ROC Curve), and F1 score are used to assess the model's performance, and the results demonstrate notable improvements over traditional CNN models like ResNet and VGG. The results show that the EfficientNet-based version achieves higher computing efficiency and improved accuracy, which makes it a good option for real-world scientific applications where precision and velocity are crucial. The paper's conclusion highlights the necessity for more research on combining EfficientNet with various advanced deep learning techniques, such as interest mechanisms, in order to likewise enhance the model's accuracy and interpretability in medical imaging tasks.

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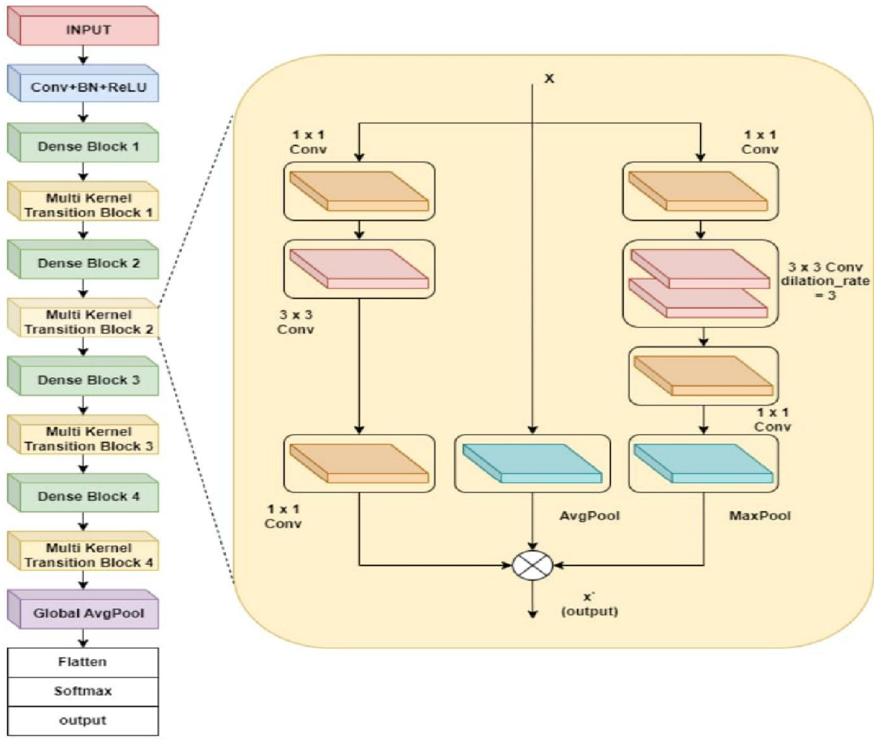
III. PROPOSED SYSTEM



The Multi-Kernel Sparse Dense Network (MKSDNet), a deep learning model created especially for classifying retinal diseases from fundus images, is represented by the architecture shown in the diagram. Superior performance in detecting subtle pathological patterns in medical images is made possible by this model, which combines the adaptability of multi-kernel convolutional modules with the potent feature reuse capabilities of DenseNet to extract a variety of spatial features.

The input image is first processed by the model using a convolutional layer, then batch normalization and a ReLU activation function. The input features are standardized and activated in this first step, setting them up for further examination. The four Dense Blocks that make up the network's structure are each composed of several densely connected convolutional layers. By guaranteeing that every layer receives input from every layer before it, these Dense Blocks maximize feature reuse and reduce the vanishing gradient issue, which enhances learning depth and efficiency.

This model's architectural innovation, Multi-Kernel Transition Blocks, are positioned in between the Dense Blocks. Every transition block uses a range of simultaneous processes to extract multi-scale features. In particular, the transition block has many convolutional paths with varying kernel sizes and configurations that process the same input. These include dilated 3×3 convolutions, which increase the receptive field without adding more parameters, and standard 1×1 and 3×3 convolutions. This enables the model to capture more contextual information.

Furthermore, statistical summaries of the features are captured by using pooling techniques, including max pooling and average pooling. A rich, multi-scale feature map that successfully encodes the global structures and local textures found in the retinal pictures is created by combining the outputs from each of these branches.

The model uses Global Average Pooling after the last Dense Block and Transition Block, which reduces the spatial dimensions of the feature maps to a single value per channel, significantly reducing the number of parameters while maintaining crucial spatial information. The output is then passed through a flattening layer and a softmax activation function, which generates a probability distribution over the output classes—indicating whether a particular retinal

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image is at risk or healthy. This hybrid architecture makes MKSDNet an effective and reliable solution for automated retinal disease diagnosis by fusing multi-kernel parallelism with DenseNet's connection pattern, which enables MKSDNet to beat traditional CNN models in both accuracy and generalization.

IV. RESULT

We performed comparative tests with popular convolutional neural network architectures such as VGG19, Xception, and ResNet18 in order to assess the performance of the suggested Multi-Kernel Sparse Dense Network (MKSDNet). Four common metrics were used to assess each model: accuracy, precision, recall, and F1 score. All models were trained and tested on the same dataset under comparable circumstances.

Performance Comparison :

Model	Accuracy	Precision	Recall	F1 Score
MKSDNet	0.990196	0.986111	1.000000	0.993007
VGG19	0.990196	0.985714	0.971831	0.993007
Xception	0.990196	0.986111	1.000000	0.993007
ResNet18	0.990196	0.985915	0.985915	0.993007

Observations :

While the performance metrics are close across models, the MKSDNet's ability to reach perfect recall without compromising precision makes it particularly reliable for early disease detection tasks. All four models demonstrated high competence in retinal disease classification with an accuracy of 99.01%. The MKSDNet outperformed in Recall (1.0), indicating it successfully identified all true positive cases — a crucial factor in medical applications where missing a diseased case can have serious consequences. F1 Scores were consistently high (0.993007) across all models, confirming balanced performance between precision and recall.

V. FUTURE SCOPE

In the future, it will be crucial to concentrate on growing the datasets used to train MKSDNet, making sure they are more extensive and varied to cover a variety of retinal conditions and populations. This will improve the generalizability and robustness of the model. Furthermore, the MKSDNet architecture will need to be continuously optimized; adding cutting-edge methods like ensemble learning or attention mechanisms could increase its precision and interpretability even further. Priority should be given to integrating the model into current clinical workflows, with an emphasis on developing intuitive user interfaces that encourage healthcare practitioners to embrace the model. Pilot tests carried out in actual environments will yield insightful criticism for improvement. Additionally important will be longitudinal studies, which will enable researchers to evaluate the model's performance over time and in real-world screening initiatives. Furthermore, investigating explainable AI methods will increase decision-making transparency and promote provider confidence. Lastly, looking into the use of MKSDNet in other medical imaging fields, such OCT or MRI analysis, may increase its usefulness and influence and enable it to identify 29 a greater variety of disorders outside of retinal diseases. The MKSDNet model can develop into a more complete tool by addressing these issues, greatly improving the early diagnosis of retinal disorders and advancing AI applications in the medical field.

VI. CONCLUSIONS

An important advancement in the early identification and categorization of retinal disorders has been made with the creation of the Multi-Kernel Sparse Dense Network (MKSDnet).

MKSDnet automates diagnostic procedures by utilizing deep learning and advanced image analysis techniques, giving medical personnel a useful tool to improve patient care.

Its potential to enhance ophthalmic results is highlighted by its capacity to evaluate big datasets and identify high-risk patients. Nonetheless, the limitations underscore the significance of further investigation and verification.

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Improving the model's dependability and acceptability in clinical settings requires addressing issues with data dependency, generalizability, and interpretability.

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[2] P. A. Keane and S. R. Sadda, ”Retinal imaging in the twenty-first century: state of the art and future directions,” Ophthalmology, vol. 121, no. 12, pp. 2489–2500, 2014.

[3] Z. Li, M. Xu, X. Yang, Y. Han, and J. Wang, ”A Multi-Label Detection Deep Learning Model with Attention-Guided Image Enhancement for Retinal Images,” Micromachines, vol. 14, no. 3, p. 705, 2023.

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