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Automatic Severity Classification of Diabetic Retinopathy Using Random Forest

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Abstract:

Diabetic Retinopathy (DR) is a severe vision-threatening condition caused by high blood glucose levels. Traditional screening by ophthalmologists can be error-prone and time-consuming, leading to increased interest in automated diagnostic methods. This paper introduces a deep learning approach that uses DenseNet169 and a Random Forest model to detect DR severity from a single-Color Fundus photograph, achieving high accuracy, sensitivity, and specificity. Trained on the Kaggle Asia Pacific Tele-Ophthalmology Society dataset, the model outperforms current methods and offers an efficient solution for autonomous DR diagnosis.

Keywords — **Dense Net169, Random Forest, Diabetic Retinopathy (DR).**

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I. INTRODUCTION

Diabetic Retinopathy is an eyes disorder in the patients suffering from diabetes. Damage to the blood veins of the retina causes this disease. Diabetic retinopathy symptoms such as Microaneurysm, Exudate Hemorrhage, Cotton Wool Spot can be seen on colour fundus retinal imaging, according to several scientific investigations. The paper presents an extension of the Medoids based modelling approach, and combines it with a Gaussian Mixture Model in an ensemble to form a hybrid classifier to improve the accuracy of the classification. Computer-Aided Screening system that analyses fundus images with varying illumination and fields of view, and generates a severity grade for diabetic retinopathy using machine learning. Classifiers such as the Gaussian Mixture Model, k-Nearest Neighbour, Support Vector Machine, and AdaBoost are analysed for classifying retinopathy lesions from non-lesions. GMM and KNN classifiers are found to be the best classifiers for bright and red lesion classification, respectively.[2]. The paper involves processing of fundus images for extraction of abnormal signs, such as area of hard exudates, area of blood vessels, bifurcation points, texture and entropies.[3]. Convolution Neural Network, which can learn hierarchical and discriminative features without clinician experience, is an alternative method to address the aforementioned issue. The paper it looks at four aspects of using deep CNN to solve the DR classification problem: network architectures, preprocessing, class imbalance, and fine-tuning.[4].

The lesion classification problem deals with unbalanced datasets and SVM or combination classifiers derived from SVM using the Dempster-Shafer theory are found to incur more classification error than the GMM and KNN classifiers due to the data imbalance. The paper provides weighted class activation maps that can illustrate the suspected position of lesions. In the pre- processing stage, eight image transformation ways are also introduced.

II. EXISTING SYSTEM

The scientific community is actively collaborating to address the challenges posed by Diabetic Retinopathy. Early detection and monitoring of the disease progression are crucial for the timely implementation of medical treatments. Medical imaging, particularly chest X-rays, plays a key role in providing essential information to specialists. X-ray images have been central to numerous studies employing artificial intelligence for the automatic classification of this condition. While the outcomes so far are promising, some studies contain errors that need correction to develop reliable models for clinical application. This work addresses certain issues identified in the current use of AI techniques for automatic classification, introducing the SVM method specifically for classifying X-ray images, which identifies and processes unlabelled data. paragraphs must be indented. All paragraphs must be justified, i.e. both left-justified and right-justified.

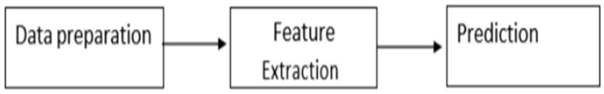

Figure:1 Deep Learning Structure

Data preparation involves transforming raw data into a format suitable for further processing and analysis. This process includes key steps such as collecting, cleaning, and labelling the data to make it appropriate for use in Machine Learning algorithms, followed by data exploration and visualization. Feature extraction involves identifying and defining the relevant features for a specific problem and implementing methods to extract these features. A solid understanding of the domain or background can significantly aid in making informed decisions about which features are most useful. Prediction refers to the output generated by an algorithm after being trained on historical data and then applied to new data, such as forecasting the likelihood of a specific outcome, like whether a customer will churn within 30 days

III.PROPOSEDSYSTEM

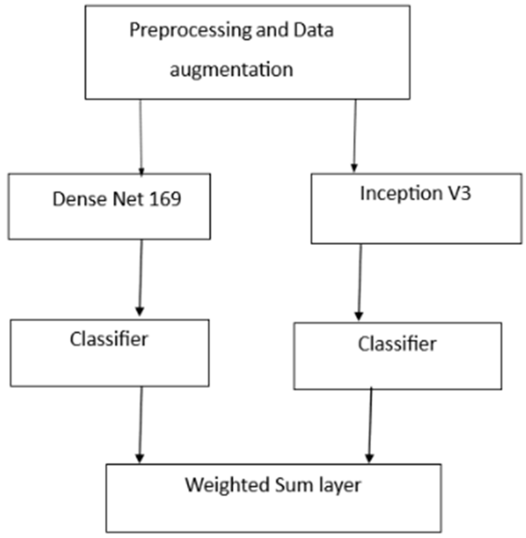

Figure: 2 Block Diagram of Proposed System

The algorithm is composed of a backbone model and an attention module. Initially, the backbone network serves as a feature extractor for the input fundus image, with features being refined through the Convolutional Block Attention Module to enhance data representation. These features are then converted into a one-dimensional array by averaging each feature map produced by the attention module using Global Average Pooling, followed by the classification head.

Data preprocessing in machine learning, involving the cleaning, transforming, and integrating of data to prepare it for analysis. This process enhances data quality and ensures it is suitable for the specific machine learning task. Since real-world data is often incomplete or inconsistent, preprocessing helps organize and format raw data for model development. The process begins with acquiring a relevant dataset, which is compiled from various sources and formatted according to the use case, such as business or medical data. Data augmentation, like using Variational Autoencoders (VAE), further enhances the dataset by generating additional data through encoding and decoding networks. Additionally, advanced models like Inception v3, a convolutional neural network, in order to assist in image analysis and object detection, advanced models like Inception v3, a convolutional neural network is used originally developed for the ImageNet Recognition Challenge

IV.RESULT

After evaluating several pre-trained models within the Dense Net family, DenseNet169 was selected for its impressive performance across all categories, owing to its efficient information transfer from lower to higher layers. To enhance performance while minimizing unnecessary complexity, in the fourth dense block the number of convolutional blocks was reduced from 32 to 12. Attention mechanisms were integrated to help the model focus on relevant features, and Random Forest was strategically positioned on top of the convolutional encoder, improving representational power while reducing training time. The dataset was split 90% for training and 10% for validation,

using stratified data splitting to maintain class distribution consistency. K-fold validation with 5 folds was employed, limiting epochs to 400 with early stopping to prevent overfitting and ensuring consistent class distribution across all folds.

V.CONCLUSION

This research presented an innovative CNN model built upon the DenseNet169 architecture, with enhancements through Random Forest to improve its representational capabilities. The proposed approach demonstrated robust performance and comparable quality metrics, all while minimizing spatial and temporal complexity. Additionally, a 2-D Gaussian filter was applied to improve the quality of fundus images, and an INS-based weighted loss function was used to address class imbalance and enhance prediction accuracy. Future research will focus on exploring different Random Forest configurations and imbalanced learning techniques, as well as increasing dataset size to further improve model performance.

VI.FUTURE ENHANCEMENT

Future improvements to the deep learning algorithm include adapting it for use in uncontrolled environments and replacing the current PCA dimensionality reduction technique with autoencoders for increased accuracy. Further testing in real-world clinical applications is needed, with the goal of making the system robust enough to operate on low-cost devices for rapid responses. Automated diagnostic approaches will continue to evolve, offering quicker diagnoses that allow doctors to consult more patients efficiently. There will be a growing demand for compact deep learning solutions with higher accuracy across multiple devices.

REFERENCES

[1] S. U. Akram, S. Khalid,’’Detection and classification of retinal lesions for grading of diabetic retinopathy” compute, Biology, Medical, vol.45, pp. 161_171, Feb.2019.

[2] S.Roychowdhury, D.D Koozekanani, “Dream Diabetic Retinopathy analysis using machine learning” IEEE J. Biomedical, Vol.18,no.5, pp.1717-1728, sep.2020

[3] M.R.K. Mookiah,” Evolutionary algorithm-based classifier parameter tuning for automatic diabetic retinopathy grading” Knowledge, Based System, vol. 39, Feb. 2018.

[4] C.Lian,Y. Liang,”Deep convolutional neural network for diabetic retinopathy classification” in procedure, 2nd Integer Advance Image processing 2018, pp.68-76.

[5] M.Shaban,Z.Ogur,A.Shalaby ”Automated staging of diabetic retinopathy using a 2D convolutional neural network,” IEEE Information Technology,Dec.2018, pp. 354-358.

[6] H.Jiang, K.Yang,”An interpretable ensemble deep learning model for diabetic retinopathy disease” Integer, Medical Biology System Jul. 2019,PP. 2045-2048.

