iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 Issue: III Month of publication: March 2024

DOI: https://doi.org/10.22214/ijraset.2024.59333

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue III Mar 2024- Available at www.ijraset.com

Automated Severity Classification Model for Diabetic Retinopathy

Ankita Kudikilla[1], Yeleti Nithin[2], Sanjeet Tumkur[3], Y. Sailaja[4]
[1, 2, 3]UG Student, Department of CSE, CMR College of Engineering & Technology, Hyderabad, Telangana
[4]Assistant Professor, Department of CSE, CMR College of Engineering & Technology, Hyderabad, Telangana

***Abstract:** Diabetic retinopathy is a serious eye disease which is caused due to high blood sugar and it eventually leads to complete blindness. Light sensing tissues of retina will be affected due to this disease. The blood vessels in the eyes will be blocked which leads to leakage of fluid in eye. This condition occurs to people having diabetics for more than a period of twenty years. This disease shows no symptoms at early stage. Later on, cloudy vision or mild blindnessmay occur. The possible cure to this disease is using detection at early stage. If it is detected earlier, we can prevent from blindness. The treatments and technologies present in today's world is time consuming. This system cannot find disease at early stage. Here we are proposing an artificial system reliant on which can anticipate the possibility of occurrence of disease using retina images. The system suggested will classify the stages of disease into five categories and produce an output accordingly. This can help in detecting diabetic retinopathy at early stage and possibly avoid the risk factor of the disease.*
***Keywords:** Diabetic retinopathy, CNN, attention mechanism, deep learning.*

I. INTRODUCTION

Diabetes Mellitus is a persistent metabolic condition characterized by heightened blood glucose levels, also known as hyperglycemia. Over time, it impacts blood vessels throughout the body on both small and large scales. According to the World Health Organization (WHO), the number of individuals with diabetes surged to 422 million in 2014, with an anticipated rise to 700 million by 2045. One of the enduring microvascular effects of diabetes is diabetic retinopathy, a progressive abnormality detected through ocular pathologies, resulting in blockages and bleeding of the retinal capillaries.. Fortunately, early detection can prevent vision impairment. However, without frequent screening, it may induce irreversible damage. International Diabetes Federation (IDF) affirmed that 93 million diabetics suffer from eye damage, yet only 200,000 ophthalmologists are available worldwide. Grading inconsistency, critical deficiency in the available number of ophthalmologists as well as the laborious process remains hindering factors for diabetic retinopathy detection.

II. RELATED WORK

Deep learning has been widely utilized in diabetic retinopathy (DR) owing to its rising of the transfer learning paradigm that offers fast convergence and performance enhancement while reducing the need for massive data and computational resources. This has opened the door for more robust algorithms in the medical domain. Gulshan V., Peng[1] developed LesionNet; the main aim of the network was to aim was to add lesion detection to severity grading to reinforce the representational power of the encoder. The architecture was built on InceptionV3, which was trained and validated using a private dataset. An ensemble stacking approach was investigated by Gardner G., Keating [5] by using five reputable architectures (Resnet50, InceptionV3, Xception, DenseNet121, DenseNet169) in order to improve produced feature maps. Furthermore, they used the Kaggle EyePACS dataset to assess the model. A hybrid deep learning model introduced by Gargeya R. [10] was built using InceptionV3 encoder for the extraction of features and then training Gaussian Process (GP) regressor to get uncertainty of the prediction using EyePACS and Messidor-2 datasets, for DR binary classification task. The EfficientNet-B3 architecturewas deployed by Quellec G., Lamard M. [7] for both binary and severity classification using APTOS dataset.

1) *Fundus Photography:* It also known as ophthalmoscopy, is a retinal examination performed by an eye care specialist. The first method involves using a slit lamp biomicroscope with a special magnifying lens to get a close-up look at the patient's retina. Alternatively, a brightly lighted headset can be worn to look through a special magnifying glass to get a wider view of the retina. A handheld ophthalmoscope is not enough to rule out diabetic retinopathy, a serious but curable condition. Larger portions of the fundus are typically captured by fundus photography, which also offers the benefit of visual documentation for future use and the ability to have the image reviewed by a professional at a different time or place.

2) *Optical Coherence Tomography (OCT):* It is a single optical imaging technique that works similarly to ultrasound and is based on interference. It creates cross-sectional images of the retina that can be used to determine the retina's thickness and to separate the main layers of the retina, making it possible to see edoema.[2]
3) *Fundus Fluorescein Angiography (FFA):* This imaging method shows staining, leakage, or nonperfusion of the retinal and choroidal arteries by relying on the circulation of D fluorescein dye.

III. METHODS AND EXPERIMENTAL DETAILS

A. Datasets

In 2019 (APTOS) dataset2 was released on the Kaggle website3 as a part of public competition for DR detection. The main aim of using fundus imaging was to classify disease severity by producing a probability that an image located in one of five clusters: No DR, Mild, Moderate, Severe, and Proliferative DR.This data was collected by Aravind Eye Hospital in India, 13,000 (approximately) images were provided at this competition; however, we had only access to the ground truth labels of 3662 images.

B. Data Pre-Processing

The uninformative black areas on the sides of the images werefirst trimmed then a circular crop was applied to have a centeredretinal image. Moreover, a filtering technique was exploited to enhance the clarity of visual bio-markers, and described by the following equations:

$X\ 00 = \alpha \times X + \beta \times X\ 0 + \gamma$…… (1)

$X\ 0 = G(\sigma x) * X$ ……(2)

X indicates the input data, $G(\sigma x)$ is a 2D Gaussian kernel with a standard deviation of $\sigma x = 15$ in x-direction and is the convolution operation. α, β, and γ were chosen empirically to be 5, −4, and 70, respectively. Ultimately, every image underwent normalization to ensure it fell within the [0, 1] range, resized to (256×256) using bilinear interpolation, and decoded to a 32-bit floating point. Fig.2 represents the input and output from the pre-processing step.

C. Data Augmentation, Balancing & Analysis

Investigating APTOS data revealed severe class imbalance, i.e., 49.29%, 10.1%, 27.28%, 5.27%, 8.05% belonging to normal, mild, moderate, severe, and proliferative DR grades. Furthermore, by its projection in lower-dimensional feature space, using Principle Component Analysis (PCA) to lower thedata dimensionality to 500-D followed by applying the t-Distributed Stochastic Neighbor Embedding (t-SNE) algorithm to analyze data distribution across different classes [40], Intuitions were developed by exploiting: Class 0 forms featureclusters all over the 2-D space, making it one of the easiest classes to be detected. Classes (1-4) have acute overlapping, which generates a challenging task for the algorithm to fit a proper hyperplane. We artificially clustered the data to form only two regions (infected and healthy), and we observed that DL, based on our understanding, is robust enough to solve the binary classification problem.

D. Training Settings

Our splitting policy was 90% to 10% of our dataset to forma training and validation set. A stratified data splitting technique was exploited to preserve the same distribution toensure the classes' distribution consistency between the aforementioned subsets and the original set. Table.4 demon stratus the training and validation data statistics. Furthermore, K-fold validation was implemented to have more robust results, and due to the size of the dataset, we used 5-folds to train on 80% and test using 20% of the original dataset at each trial. Furthermore, the maximum number of epochs was limited to 400 while using an early stopping callback to avoid overfitting by saving the best weights corresponding to the minimum validation loss. Finally, we used the exact stratified data splitting mechanism to ensure the same class distribution at each fold.

IV. LITERATURE SURVEY

Machine learning techniques have been employed for the purpose of forecasting the occurrence of Diabetic Retinopathy. Here among many possible classification algorithms, they have used four algorithms namely, Naive Bayes , Decision Tree, K-Nearest Neighbor and Support Vector Machine. Each of the algorithms have certain advantages and disadvantages specific to the type of applications. However, the results indicated that, support vector machine had the highest accuracy among the rest, closelyfollowed by KNN. The remaining algorithms exhibited average performance on the test dataset when utilizing specific parameters. However, there were limitations in the approach regarding both the number of attributes employed and how these attributes were depicted.

The methods of data mining have been kindly utilised in the past for medical diagnosis and prognosis. The primary focus of this effort is the feature By using image processing techniques to extract information from retinal pictures, relevance and classification approaches can be applied to accurately classify retinal diseases. Apart from this, a thorough analysis of feature relevance and classification techniques has been carried out to support the claim that the Random Tree algorithm and C4.5 classifiers are the most accurate in predicting retinal image dataset diseases.

The proposed prediction algorithm for diabetic retinopathy derived from a dataset of eye images from diabetic patients and a few algorithms. For feature extraction from photos, they used support vector machines, naive Bayes, and local binary patterns. machine learning techniques to categorise patient information since. Medical data is expanding rapidly, and this data must be processed in order to forecast the precise disease based on symptoms. By providing the input, they were able to accurately detect diabetic retinopathy or not.

Patients' retinal images are utilized to assess the stage of diabetic retinopathy. A comparison was made between the performance of naive Bayes and SVM algorithms concerning accuracy, memory usage, and processing time. The SVM algorithm exhibited higher accuracy than the naive Bayes algorithm, with a shorter classification time and lower memory requirements. Notably, one of these models achieved an area under the curve of 0.79. Intriguingly, the study's findings underscore the significance of predictive signals located in the peripheral retinal fields, Which are usually not encompassed within diabetic retinopathy assessments. These findings demonstrate the potential for predicting future progression of diabetic retinopathy. Continued advancements with extensive and varied image datasets could empower algorithms like this to facilitate early detection and prompt referral to a retina specialist for increased monitoring and potential early intervention. Additionally, it could enhance patient enrollment in clinical trials aimed at addressing diabetic retinopathy.

A diabetic retinopathy tool based on artificial intelligence is outlined, aiming to aid clinicians in swiftly analyzing fundus images to inform subsequent steps in patient treatment. This tool also enables doctors to allocate attention to more patients requiring medical intervention. Emerging healthcare technologies prioritize minimizing visits to eye specialists, thus reducing overall treatment costs and maximizing the number of patients each doctor can attend to. Artificial intelligence plays a crucial role in assisting healthcare professionals in achieving this objective. However, it should not entirely replace clinicians at its current stage. Ongoing advancements in the

The field of artificial intelligence is presenting new opportunities for implementing algorithms to detect and grade diabetic retinopathy. This study focuses on diabetic retinopathy detection, aiming to identify the most effective classification algorithms and to generate a comprehensive dataset to minimize errors. The research evaluates various Comparing algorithms designed for detecting diabetic complications such as heart disease, retinopathy, diabetic foot issues, neuropathy, and nephropathy. A total of nine algorithms were evaluated in the study., with the findings revealing Random Forest as the most accurate predictor for Type 3 diabetes complications in many instances, while Naive Bayes performed the least effectively.

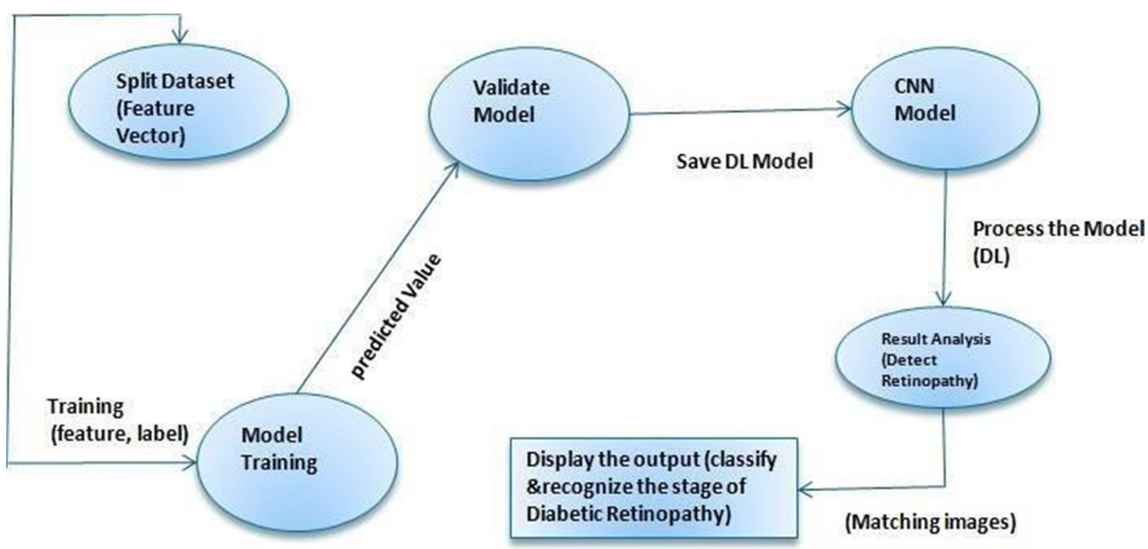

Fig.1.

V. RESULTS AND DISCUSSIONS

It is easier for our model to be distorted and have robust behavior only in detecting major classes (0 and 2) and viceversa. Attaching CBAM to our encoder enhanced the detection of classes 1 and 3 by 44.2%, 43.24% . An average QWK and accuracy values of 0.8072 and 72.3% were achieved, respectively, using the 5-fold k-validation technique,we trained our algorithm only for 400 epochs to reduce the computational cost of training five different models, further training will provide more intact results. As the proposed method outperformed the literature work on the severity grading task and showed comparable results. Our model enhanced accuracy and QWK by 0.4% and 24.9% while decreasing inference time by cutting down the number ofparameters by 83% compared to [8]. We achieved almost the same accuracy as [9] while reducing the model size. Our best trial had an increase in accuracy of about 7% compared to the AM-InceptionV3 [7] method.

SFTL model achieved high accuracy at the severity grading task. Nevertheless, they did not address the issue of data.imbalance. EfficientNet-B3 [6] achieved higher accuracy but only for major classes, while we achieved comparable accuracyin minor classes, and finally, We compared our best trial with the MSA network without multi-level feature reuse [3]. We had almost the same accuracy with an increase in QWK by 3.6%. Furthermore, we achieved a better confusion matrix across all classes than the literature while reducing time and space complexity by a 45% reduction in parameters. Severity gradingf1-score was not mentioned in the literature. However, by using CBAM and INS, an enhancement was established with respect to the baseline DenseNet169. Our algorithm demonstrated robustness against other deep learning architectures for the binary classification task. Above all, the literature did not deal with the class imbalance problem. Most of the algorithmsimplemented did not consider its effect on quality metrics which provided overestimated outcomes, as most of them werepredicting perfectly only for major classes due to ignoring data inherited imbalance. Furthermore, binary grading did not require complex architectures to solve it, our algorithm with lower parameters achieved almost the same metrics compared to other algorithms, plus when we artificially formed twoclusters (infected and normal), the classes were balanced whichhelped literature algorithms to excel in such a task. Moreover, our algorithm exceeds the minimum limits provided by English National Screening Programme for sensitivity allowed better performance, class 1,3 detection is enhanced by 43.3% respectively, with respect to the baseline algorithm. Finally, using CBAM with DenseNet169 while adding weighted loss has demonstrated thriving performance across all classes. Regardless of the reduction in class 2 by 14.63%, classes (1,3 and 4) exhibit significant improvements.

VI. CONCLUSION

In this study, we exploited a new CNN model based on DenseNet169 architecture integrated with CBAM as an additional component to be added for representational power enhancement. The proposed method demonstrated robust performance and comparable quality metrics while reducing the burden of space and time complexity. Furthermore, a 2-D Gaussian filter enhances fundus images' quality. Finally, we used INS to form our weighted loss function to attack the classimbalance to improve the model's prediction across all classes.For future research direction, we evaluate the performance of different CBAM configurations. Moreover, experimenting withdifferent imbalanced learning techniques and increasing the dataset size will lead to better performance.

REFERENCES

[1] "Gulshan V., Peng L., Coram M., Stumpe M. C., Wu D., Narayanaswamy A., Venugopalan S., Widner K.,Madams T., Cuadros J, 2016
[2] Xu Y., Xiao T., Zhang J., Yang K., Zhang Z. Scale-invariant convolutional neural networks. arXiv preprintarXiv:1411.6369, 2014 .
[3] Yosinski J., Clune J., Nguyen A., Fuchs T., Lipson H. Gaining insights into neural networks via profound comprehension. visualization. arXiv preprint arXiv:1506.06579, 2015 .
[4] Abràmoff M. D., Reinhardt J. M., Russell S. R., Folk J. C., Mahajan V. B., Niemeijer M., Quellec G. Automated early detection of diabetic retinopathy. Ophthalmology, 2010.
[5] Gardner G., Keating D., Williamson T., Elliott A. Detection of diabetic retinopathy using an artificial neural network: a screening tool with automated capabilities. (Source: British Journal of Ophthalmology, 1996).
[6] Microaneurysm detection and diabetic retinopathy grading. IEEE transactions on biomedical engineering, 2012.
[7] UR A. Decision support system for diabetic retinopathy using discrete wavelet transform. Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, 2013
[8] Gulshan V., Peng L., Coram M., Stumpe M. C., Wu D., Narayanaswamy A., Venugopalan S., Widner K., Madams T., Cuadros J., et al. Development and validation of a deep learningalgorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 2016
[9] Gargeya R, Leng T. Automated identification ofdiabetic retinopathy using deep learning. Elsevier 2017
[10] Fluorescein Angiography Insight and SerendipityHalf Century Ago by Michael F. Marmor, MD; James G. Ravin, MD.
[11] Optical Coherence Tomography: A nascent technology for biomedical imaging and optical biopsy.by James G Fujimoto,* Costas Pitris,*† and Mark E Brezinski
[12] Abràmoff M. D., Reinhardt J. M., Russell S. R., J. C., Mahajan V. B., Niemeijer M., Quellec G.Automated early detection of DR.
[13] Deep learning algorithm predicts DR progressionIn individual patients, Zdenka haskova, Marco Prumotto