Detection of Diabetic Retinopathy using Multi-label Feature Extraction and Classification with Fully Homomorphic Encryption

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KEYWORDS

ABSTRACT:

Diabetic Retinopathy (DR) is a circumstance that develops as a consequence of prolonged diabetes, directly impacting or implicating human vision. In its early stages, Diabetic Retinopathy (DR) typically presents no symptoms, and its progression can ultimately result in irreversible vision loss if not diagnosed and treated promptly. The computer supported the conclusion with the help of clinical pictures to help in provoke and exact treatment. Microaneurysms (MA) show the starting of DR, making it a significant calculate in diagnosing the malady. With the progression of Internet of Things (IoT), countless electronic gadgets are connected with the Internet. These associated electronic devices acquire and communicate data, and answer to any activities. In the medical system, hospitals can execute medical diagnosis (MD) with medical sensors, specially for inaccessible supporting MD. But, in this circumstance, patients' privacy (PP) is of supreme importance, and privacy of medical data is decisive. Hence, the fundamental challenge ahead is the way to acknowledge distant assistant MD while safeguarding confidentiality of the clinical information and guaranteeing PP.

1.1Introduction:

In the last 20 years, the prevalence of diabetes has risen significantly in recent years, raising concerns globally. The IDF Diabetes Atlas reports an alarming statistic, indicating that Worldwide, close to 500 million individuals across all age groups have received a diagnosis of diabetes, with projections estimating this number to soar to seven hundred million by the end of 2045. This escalation poses a substantial global health challenge. Moreover, Based on data from the IDF Diabetes Atlas, it is anticipated that by the conclusion of 2040, one in three individuals with diabetes will be affected by Diabetic Retinopathy (DR), a condition characterized by damaged blood vessels located behind the retina. If left untreated for an extended period, DR can lead to severe complications, including vision loss, highlighting the urgent importance of early detection and intervention[1].

Presently, medical professionals rely on manual examination of fundus images to estimate the critical nature of DR, a process that is prolonged and constrained by a shortage of trained personnel relative to the growing patient population. As a result, numerous patients fail to receive prompt medical attention, with cases often remaining undetected until the disease reaches an advanced stage. Despite physicians' recommendations for regular fungus screenings for diabetic individuals, a significant number of cases slip through the cracks until the condition becomes critical. In this manner, there's an pressing request for an mechanized system to help within the location of diabetic retinopathy, guaranteeing provoke mediation and improving quiet results [2].

The majority of research in this domain relies on fundus images, that serve as visual records documenting the current ophthalmic condition of an individual's retina. These images are pivotal for identifying diabetic retinopathy (DR) through a series of steps including retinal blood vessel segmentation, DR detection and lesion segmentation [3]. The presence or absence of various lesions within these fundus images can indicate the presence and stage of DR. Key lesions in diabetic retinopathy include microaneurysms (MAs), superficial retinal hemorrhages (SRHs), exudates (Exs), which consist of both soft exudates (SEs) and hard exudates (HEs), intraretinal hemorrhages (IHEs), and cotton wool spots (CWSs). Figure 1 compares the appearance of a sound retina with that of an unfortunate retina, highlighting the significance of these injuries in diagnosing diabetic retinopathy (DR).

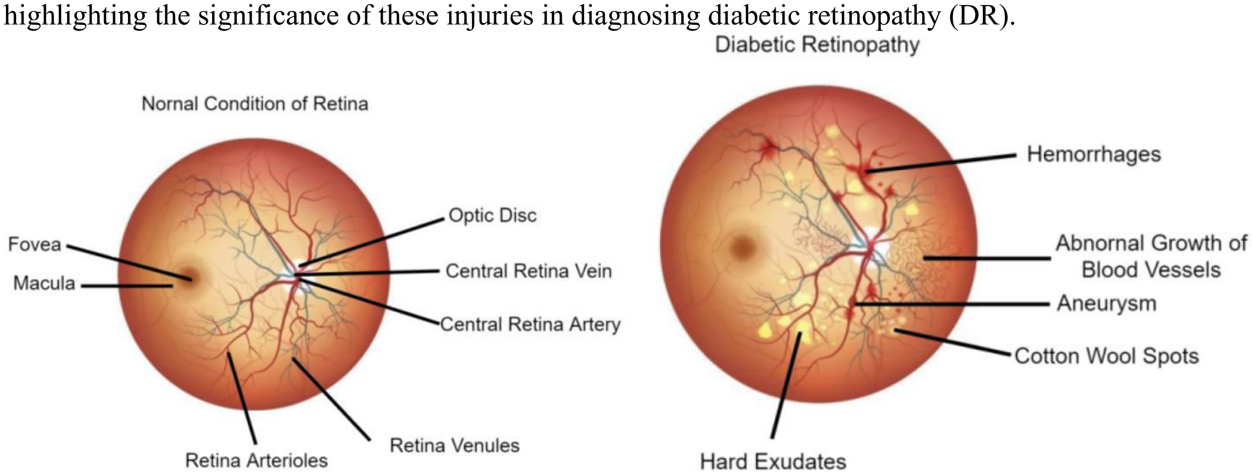

Figure 1: Healthy Retina and Affected Retina

These techniques leverage vast datasets of annotated fundus images to train models that can effectively identify and classify various lesions associated with DR, such as micro aneurysms, hemorrhages, and exudates. By analyzing subtle patterns and features within these images, machine learning algorithms can differentiate between healthy and diseased retinas, as well as classify the severity of DR.

Machine learning, which is a superset of Deep learning, has further enhanced the performance of DR classification systems by self-learning hierarchical models of features from raw image data. Convolutional Neural Systems (CNNs) are a commonly utilized design in profound learning, excel at image recognition tasks and have been successfully applied to DR detection and grading.

Overall, the incorporation of AI methods, especially machine learning and deep learning, has significantly improved the efficiency and accuracy of retinal disease diagnosis, paving the way for prompt identification and treatment to avert vision loss in individuals with diabetes. Diagnosis of diabetic retinopathy involves two primary techniques: detection and grading. Detection entails binary classification, distinguishing between diabetic retinopathy (DR) and a normal retina. On the other hand, grading involves identifying and annotating the affected areas within the retina, along with categorizing the severity of the infection, which may include classifications such as mild, moderate, or severe[4]. These techniques are crucial for accurately assessing the presence and extent of diabetic retinopathy, facilitating appropriate treatment and management strategies for patients[18].

Security in medical image processing is paramount due to the delicate nature of medical information and the potential implications of unauthorized access or tampering. Several key considerations for ensuring security in medical image processing including Data Encryption. Implementing encryption techniques to protect medical image data both during storage and transmission helps safeguard against illegal access. Encryption confirms that only certified individuals with the proper decryption keys can access and view the images. Here we proposed the most secure encryption technique called Homomorphic encryption[5].

1.2 Homomorphic Encryption:

This encryption stands as a cryptographic technique that enables users to perform binary computations on Encrypted data that can be processed without the requirement of decryption beforehand. This means that users can manipulate and process encrypted data while maintaining its confidentiality, allowing for secure computations on sensitive information[6]. In concentrating, homomorphic encryption converts a set of data into code, enabling data examination without compromising privacy. Three primary types of homomorphic encryption exist, Each of these types leverages changes or developments of public key cryptography to securely encrypt and decrypt data.

In practical applications, homomorphic encryption enables the subdivision of encrypted data, providing one key to decrypt the total dataset and several other keys to decrypt specific subparts. This allows for different pieces of encrypted data to be accessed or processed independently by various individuals. As a result, users gain more straight control over the privacy of the encrypted data, enhancing confidentiality and security [7].

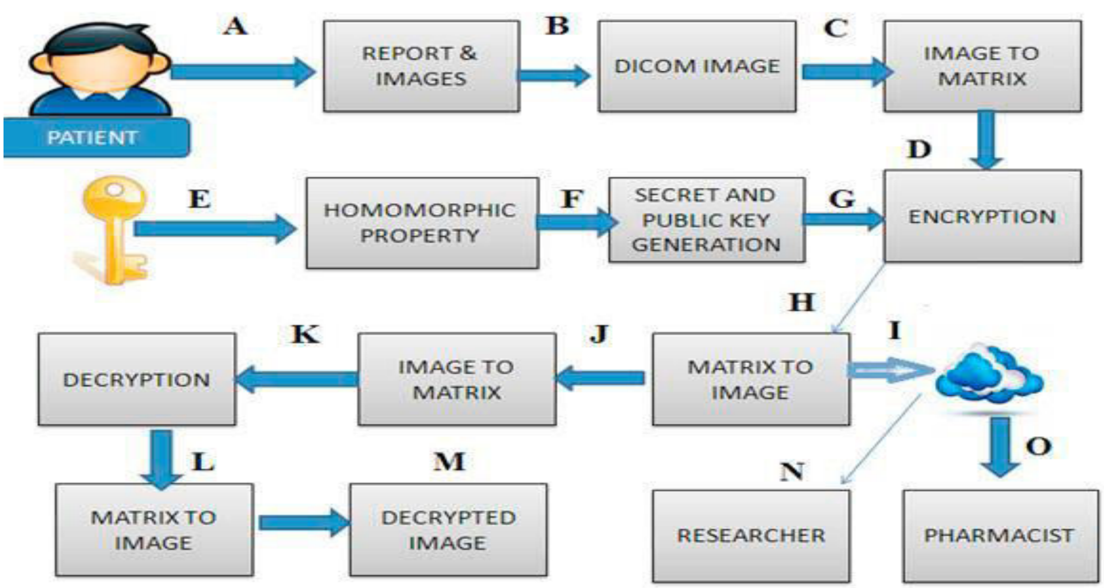

Figure 2: Encryption and Decryption in Homomorphic Encryption

Somewhat homomorphic encryption faces limitations when the ciphertext generates excessive noise in the data, which can hinder accurate decryption and computation of results. The presence of increased noise results in greater computational overhead, slowing down the functionality of the encryption scheme. Another constraint is the multiplicative depth, this denotes the highest number of multiplications a somewhat homomorphic encryption scheme can achieve. Despite these limitations, somewhat homomorphic encryption remains useful, particularly in physics applications involving coherent states.

The types of homomorphic Encryption are listed below.

1.2.1 Partial Homomorphic Encryption(PHE): It allows for either one operation, such as multiplication or addition, to be performed on ciphertext data an countless timeswhereaskeeping up the security and protection of the information.

1.2.2 **Somewhat Homomorphic Encryption(SHE):**Which bolsters both expansion and increase on ciphertext, in spite of the fact thatas it were for a restricted count of operations.

1.2.3 Fully Homomorphic Encryption(FHE): Completely Homomorphic Encryption (FHE) permits for the boundless execution of expansion and increase operations on scrambled information, while preserving its confidentiality. Moreover, FHE permits any type of computation to be performed on the encrypted information, providing a high level of flexibility and utility in various applications

Difference between Fully Homomorphic Encryption and Somewhat Encryption

The initial creation of fully homomorphic encryption began with a somewhat homomorphic encryption scheme as its foundational component. Although the mathematical principles underlying both encryption schemes are similar, their functionalities vary significantly. The primary distinction between fully homomorphic encryption and limitations of somewhat encryption stem from its capacity restrictions. Somewhat homomorphic encryption can only process simple mathematical expressions on encrypted information, mainly because of the accumulation of interference in the ciphertext. [5].

These distinct encryption schemes operate within different scopes, sometimes even within the same field. A relevant example is the difference between stationary and mobile 5G networks. Somewhat homomorphic encryption is well-suited for stationary networks, which are defined by more limited data paths and fewer processing elements. Conversely, fully homomorphic encryption would be preferred for mobile networks, as it doesn't face the same limitations on homomorphic operations [6]. Completely Homomorphic Encryption (FHE) permits for an boundless number of operations to be performed on scrambled information, supporting both addition and multiplication processes. Apart from that, somewhat homomorphic encryption (SHE) has limitations on the number of operations it can perform, permits either expansion or duplication to be performed on scrambled information, but not both, and frequently forces confinements on the number of times these operations can be iterated. This distinction makes FHE more versatile for unlimited computations on encrypted information.

Fully homomorphic encryption (FHE) provides the greatest degree of versatility and strength compared to the other two forms of homomorphic encryption. It allows the assessment of any circuit made up of various gate types, such as AND, OR, and NOT gates, with an unbounded depth. This implies that FHE enables Advanced calculations can be performed on scrambled information without the require for unscrambling, making it exceptionally versatile for various applications requiring privacy-preserving computations [7]. FHE offers a powerful solution for preserving privacy and security, even in situations with limited bandwidth, high mobility, and varying network conditions. Its ability to handle arbitrary computations on encrypted data makes it well-suited for mitigating the unique challenges posed by mobile networks, thus enhancing overall data security in such environments. [8].

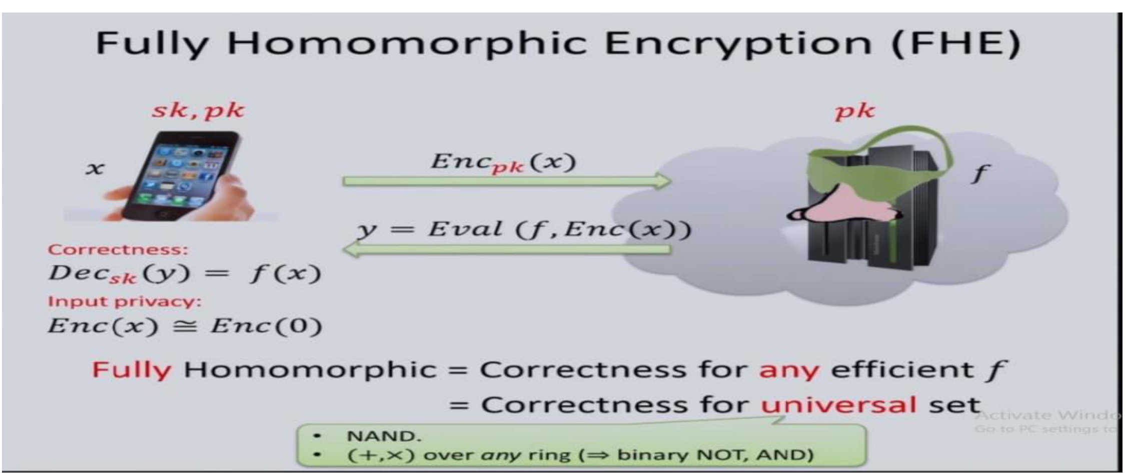

Figure 3: Homomorphic Encryption

1.2.4 Retina dataset

Multiple publicly accessible datasets exist for the analysis of retinal images aimed at detecting Diabetic Retinopathy and identifying blood vessels. These datasets are essential assets for training purposes, validating, and testing models, as well as for benchmarking a system's efficiency in relation to other models. Retinal imaging encompasses various modalities, including retinal fundus images and optical coherence tomography (OCT). Optical Coherence Tomography OCT images are two-dimensional and three-dimensional visualizations of the retina obtained using non-coherent light, providing crucial information about retinal architecture and thickness. Conversely, fundus images are two-dimensional representations of the retina captured using reflected light. In recent years, OCT retinal imaging has become increasingly significant. Furthermore, various freely accessible fundus picture datasets are broadly utilized in inquire about and analysis[10]. A few of the well-known fundus picture datasets include:

DIARETDB1 : This dataset comprises 89 publicly accessible retina fundus images, each sized at 1500 × 1152 pixels and merged with a 50-degree field of view (FOV). Within this collection, there are 84 images depicting Diabetic Retinopathy cases, while the remaining five images showcase normal retinal conditions. Notably, these images have been meticulously examined and annotated by four clinical specialists for accurate classification and analysis.

Kaggle :This dataset contains 88,702 high-resolution pictures captured with different cameras, including resolutions extending from 433 × 289 pixels to 5184 × 3456 pixels. These images have been carefully categorized into five distinct stages of diabetic retinopathy. Notably, while all images are included in the dataset, only training images provide comprehensive insights and are freely accessible. It's worth mentioning that caution is advised when utilizing Kaggle, as it might include images of lower quality and possibly inaccurate labeling.

E-ophtha :This publicly available dataset is divided into two subsets: E-ophtha EX and E-ophtha MA. The E-ophtha EX subset contains 47 images of exudates (EX) and 35 images of healthy retinal conditions, while the E-ophtha MA subset includes 148 images of microaneurysms (MA) and 233 images of normal retinal conditions.

DDR : The DDR dataset comprises 13,673 fundus images collected from 147 hospitals across 23 provinces in China. These images are classified into five stages of diabetic retinopathy (DR) severity: no DR, mild DR, moderate DR, severe DR, and proliferative DR. Additionally, a sixth category is designated for poor-quality images, though such images have been excluded from the dataset provided here. Furthermore, all images have undergone preprocessing to remove any black background. Within this dataset, 757 images have been meticulously labeled to highlight DR lesions.

DRIVE :This openly available dataset is designed for blood vessel segmentation tasks. It contains 40 images taken with a 45-degree field of view (FOV), each with dimensions of 565 × 584 pixels. Among these, seven images show cases of mild Diabetic Retinopathy (DR), while the rest display normal retinal images.

HRF : The dataset involving in blood vessel segmentation tasks comprises 45 publicly available images, each sized at 3504 × 2336 pixels. Among these images, there are 15 depicting Diabetic Retinopathy (DR), 15 showcasing healthy retinal conditions, and an additional 15 featuring cases of glaucoma.

MESSIDOR: The publicly available dataset for Diabetic Retinopathy includes two versions: Messidor-1 and Messidor-2. Here's a brief overview of each.
Messidor*-1*: The publicly available dataset described here comprises 1200 retinal color images obtained at a 45-degree field of view (FOV), meticulously annotated to four stages of Diabetic Retinopathy (DR). These datasets, provided by partners of the Messidor program, have been curated to support research on computer-aided diagnosis of diabetic retinopathy[10]. Messidor-1, one of the datasets in question, includes 1200 eye images captured using RGB imaging. These images were sourced from three ophthalmologic departments, with 800 images taken after pupil dilation and 400 images without dilation. Each image is linked to two diagnoses or labels:
i. Retinopathy grade, categorized into four stages (0, 1, 2, and 3)
ii. Likelihood of macular edema, categorized into three levels (0, 1, and 2)
This dataset is an important resource for research focused on creating computer-aided diagnostic tools for diabetic retinopathy, promoting progress in disease detection and management.
Messidor-2 : The publicly available dataset mentioned contains a total of 1748 images captured at a 45-degree field of view (FOV). Messidor-2 serves as an extension to Messidor-1, incorporating additional images from examinations conducted at Brest University Hospital in France.
Out of the 1748 images in Messidor-2:

- 1058 images are sourced from the original Messidor dataset.
- 690 images were acquired at the Ophthalmology department of Brest University Hospital between October 16, 2009, and September 6, 2010

These images were captured using non-mydriatic fundus cameras with a 45-degree FOV.
The Messidor-2 dataset includes one folder containing various images and a CSV file with four columns, as follows:
a) 1744 unique values
b) Diagnosis (for Retinopathy) which consists of grade "0" of 1017 numbers, grade "1" of 270 numbers, grade "2" of 347 numbers, grade "3" of 75 numbers and grade "4" of 35 numbers.
c) Dme (for Edema) which consists of grade "0" 1593 numbers and grade "1" of 151 numbers.
d) Grade
STARE : The segmentation of blood vessels dataset includes 20 images captured at a 35-degree field of view (FOV), each with a resolution of 700 × 605 pixels. Among these, 10 images depict normal retinal conditions.

CHASE DB1 :A publicly accessible dataset for blood vessel segmentation contains 28 images, each one with a resolution of 1280 × 960 pixels, captured at a 30-degree field of view (FOV).

"Indian Diabetic Retinopathy Image dataset" (IDRiD) :The openly accessible dataset outlined here includes 516 fundus images, acquired at a 50-degree field of view (FOV), meticulously labeled to represent five stages of Diabetic Retinopathy (DR).

ROC : The dataset comprises 100 publicly available retina images acquired at a 45-degree field of view (FOV). These images vary in size, ranging from 768 × 576 to 1389 × 1383 pixels. They have been meticulously annotated to facilitate the detection of microaneurysms (MA). However, only training ground truths are provided for this purpose.

DR2 : The dataset consists of 435 openly accessible retinal images, each sized at 857 × 569 pixels. These images come with referral annotations, indicating whether they require further examination or referral for potential issues. Among these images, 98 have been graded as requiring referral.

2. Related Work

A Convolutional Neural Network (CNN) was used to classify the images from the Kaggle dataset as either normal or exhibiting signs of diabetic retinopathy. (DR). A total of 1,000 images from the dataset were used for this purpose. Prior to feeding the images into the CNN model, data augmentation techniques were applied, and the images were scaled to dimensions of 224×224×3. Various techniques, including rescaling, shearing, rotation, flipping, and translation, were applied to augment the dataset, thereby increasing the number of available images. The CNN architecture comprised four max-pooling layers, eight convolutional layers (CONV layers), and two fully connected (FC) layers. Then the SoftMax function was used in the final layer of the CNN for classification purposes. This approach yielded an accuracy of 94.5%. Each image was categorized as either non-referable DR or referable DR based on the model's predictions[11].Here the author has proposed some pre-trained Deep Learning Multi-Label Feature Extraction and Classification model referred to as, ResNet50, ResNet152, and SqueezeNet1 which was built upon a pre-trained Convolutional Neural Network (CNN) architecture. The results from the experiment showed a accuracy of 93.67percentfor ResNet 50, an accuracy of 91.94% for Squeezenet1 and an accuracy of 94.40% by ResNet152 underscores the model's suitability for integration into routine clinical settings and its potential to bolster extensive diabetic retinopathy (DR) screening initiatives[12]. Applying ResNet 3, Gausian filter and image normalization to a binary classification that model revealed an accuracy of 85% and sensitivity of 86% [13]. When the author applied to ResNet 50 they got the AUC=96.3%; Accuracy=92.6%; and Sensitivity = 92%. Their network was evaluated on two widely recognized benchmark datasets: the ISBI 2018 IDRiD challenge dataset and the Messidor dataset. In the evaluation, their method demonstrated superior performance compared to other approaches. Specifically, their method achieved the highest performance on the ISBI 2018 IDRiD competition dataset, showcasing its effectiveness in accurately classifying images within this dataset. Additionally, their method surpassed other existing methods when evaluated on the Messidor dataset, further highlighting its robustness and efficacy in diabetic retinopathy detection. Overall, these results underscore the effectiveness and superiority of our method in accurately identifying diabetic retinopathy from medical images, as demonstrated through rigorous evaluation on established benchmark datasets[14].

3. Methodology:

This paper introduces an innovative deep learning-based Multi-level Feature Extraction and Classification (ML-FEC) model developed to detect and classify diabetic retinopathy (DR) lesions in color fundus images (CFPs) across all five stages of DR. In contrast to conventional classification techniques, this model employs a multi-label classification approach, recognizing that the expected outputs (predictions) may include zero or more class labels that are not mutually exclusive. By leveraging deep learning techniques, particularly within the ML-FEC framework, the model demonstrates enhanced capabilities in identifying and categorizing DR lesions accurately, catering to the diverse manifestations across different stages of the disease. This multi-label classification methodology enables more nuanced and comprehensive analysis of CFPs, allowing for the identification of various DR lesions simultaneously, thereby facilitating a more holistic understanding of the disease progression.The annotation process for each image was meticulously conducted by a panel of experts and recorded in Excel files. Each image within the dataset is associated with a diagnosis ranging from "No DR" (No Diabetic Retinopathy) to various stages of severity including "Mild NPDR" (Non-Proliferative Diabetic Retinopathy), "Moderate NPDR", "Severe NPDR", "Early PDR" (Proliferative Diabetic Retinopathy), and "High-risk PDR". Furthermore, the annotations involve identifying specific diabetic retinopathy lesions present in the images. Figure 4 illustrates the structured organization of the dataset along with representative samples of retinal images, highlighting their unique features and corresponding classifications as recorded in the Excel files.

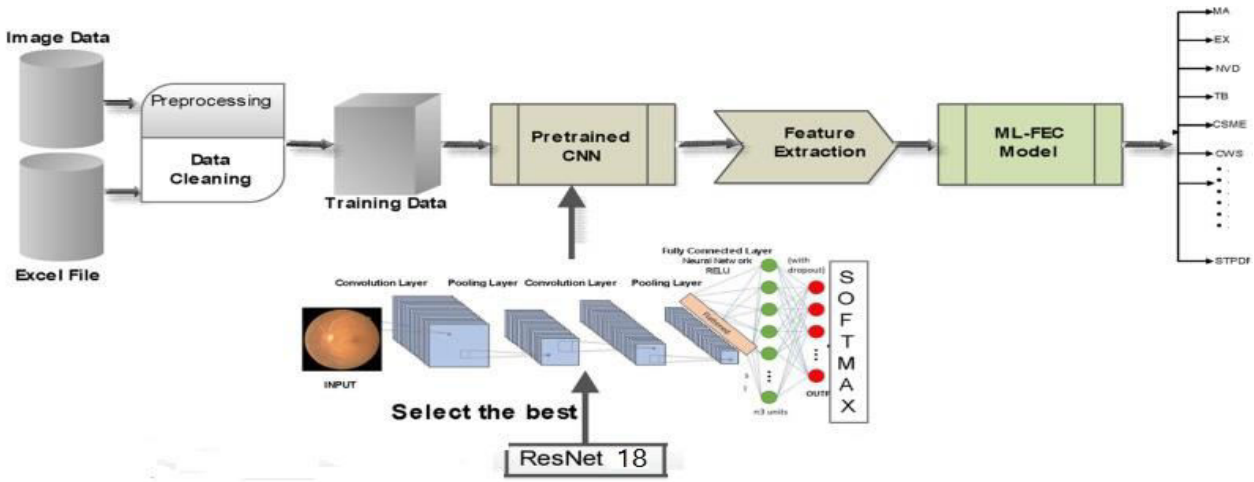

Figure 4: ***Deep learning multi-label feature extraction and classification (ML-FEC) model***

3.1 Dataset:

In this work we have taken Messidor-2 dataset having one Image folder where different images DR are stored and one csv file which have four columns as follows

i) 1744 unique values

ii) Diagnosis (for Retinopathy) which consists of grade like:

retinopathy_grade = {0: 'None', 1: 'Mild DR', 2: 'Moderate DR', 3: 'Severe DR', 4: 'PDR'}

"0" of 1017 numbers, grade "1" of 270 numbers, grade "2" of 347 numbers, grade "3" of 75 numbers and grade "4" of 35 numbers.

iii) Dme (for Edema) which consists of grade

diabetic_macular_edema = {0: 'No Referable DME', 1: 'Referable DME'}

"0" 1593 numbers and grade "1" of 151 numbers.

The data of Messidor dataset is distributed in different grade of retinopathy like None, Mild DR, Moderate DR, Severe DR, PDR andand various stages of Edema like No Referable DME and Referable DME. whose pictorial representation is placed below in Figure 4.

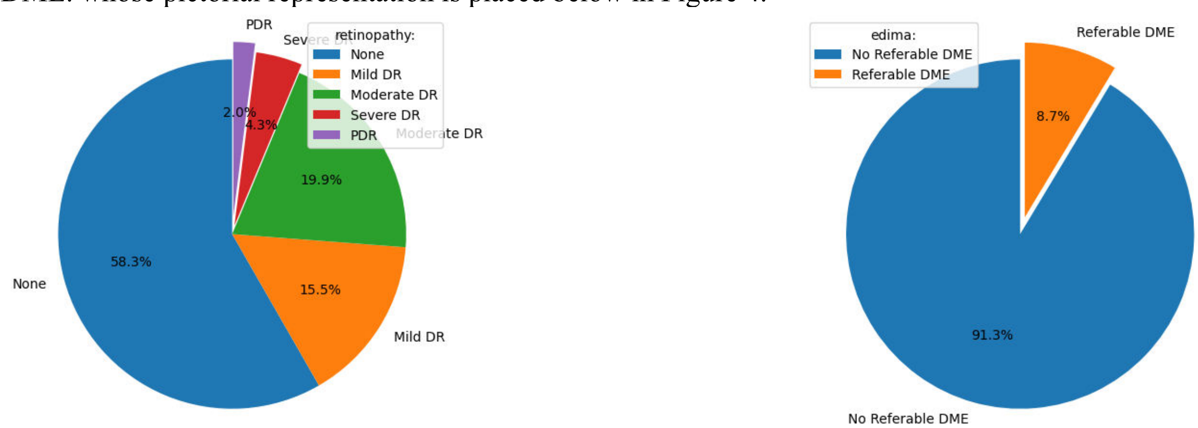

Figure:5 Retinopathy and Edema

3.1.1 Data Augmentation

Data augmentation is especially useful when you have a limited amount of labeled data, as it allows you to artificially enlarge the dataset and enhance the model's capacity to generalize. It is widely applied in deep learning tasks, such as training convolutional neural networks (CNNs) for image classification, object detection, and segmentation. Each image is augmented by HorizontalFlip, VerticalFlip, Rotate, ToGray, GaussNoise, ChannelShuffle, CLAHE. One row of augmented data is presented below in Figure 5.

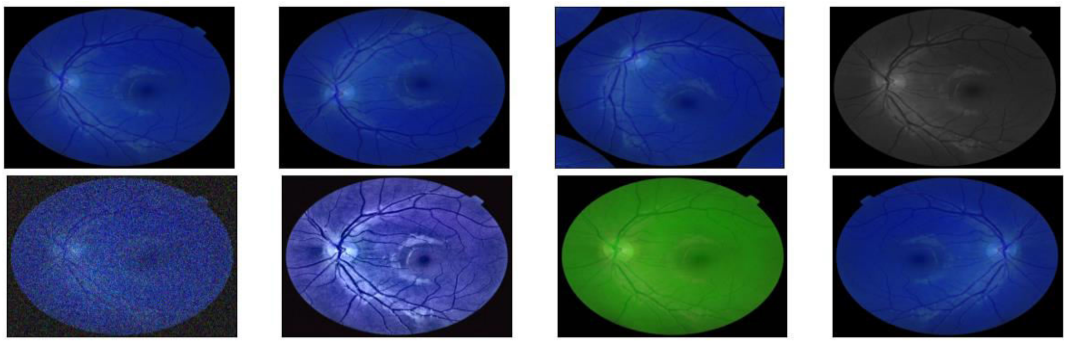

Figure 6 Augmented Sample Image

When we applied augmentation to the Retinopathy and Edema dataset as this is multilevel classification so the data will be augmented. The resultant data generated after augmentation is as follows:
'None': 1017, 'Mild DR': 318, 'Moderate DR': 863, 'Severe DR': 777, 'PDR': 335, which is equal to 3310 numbers of Retinopathy images. The pictorial presentation of the augmented dataset is placed below in Figure 6.

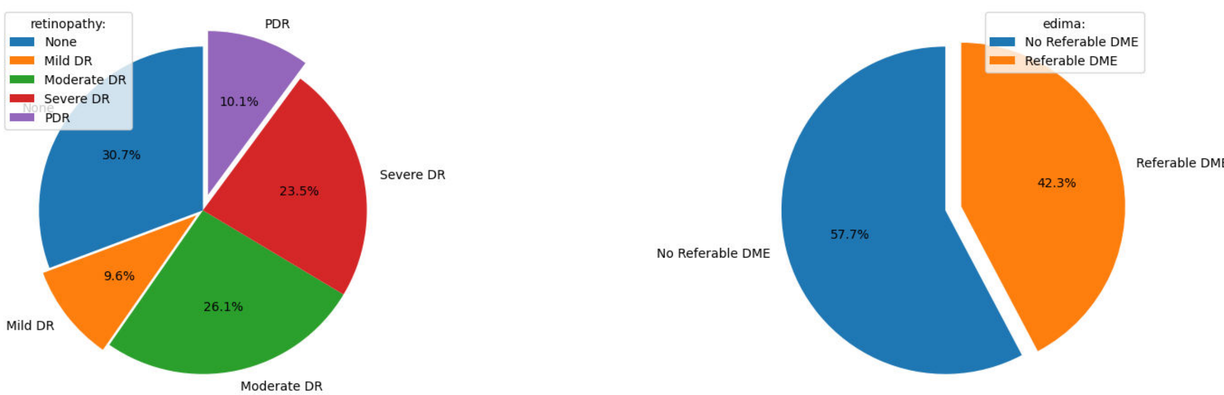

Figure: 7 Retinopathy and Edema after augmentation

3.2 Transfer Learning Approach using ResNet 18

Transfer learning is a key machine learning technique that involves adapting a model originally trained for one task to be used for a different, but related, task. In the context of image classification, ResNet (Residual Network) is a widely used deep learning architecture recognized for its efficiency and effectiveness. ResNet18 is characterized by its 18-layer architecture, where the first layer employs a 7x7 kernel. The network consists of four identical ConvNet layers, each containing two residual blocks. Each block includes two weight layers, with a skip connection that links the output of the second weight layer to the ReLU activation. If the output of the block matches the input of the ConvNet layer, the identity connection is employed. Furthermore, if there is a mismatch between the input and output, a convolutional pooling operation is applied to the skip connection. The input dimensions accepted by ResNet18 are (224, 224, 3), representing the width, height, and RGB channels, respectively. The final layer of the network is a fully connected (FC) layer, which passes its output into the subsequent sequential layer [15]. This architectural design with residual blocks and skip connections contributes to the network's ability to handle vanishing gradient issues and facilitates the training of deep neural networks[16,17].

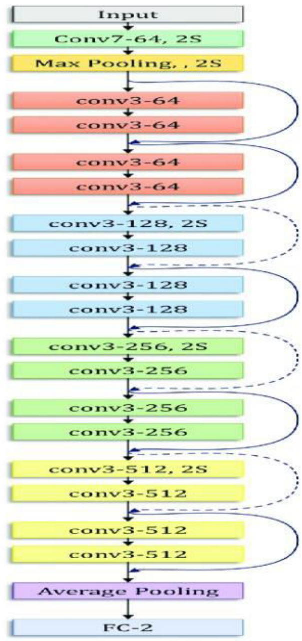

Figure: 8 Architecture of ResNet 18

4 Results and Discussion

The proposed method was implemented using Python 3 on the Google Colaboratory platform, utilizing a system with Windows 10, 8GB of RAM, and an i3 processor. During the training of the CNN model, a test accuracy of 95.1 percent was achieved. Table 1 shows the confusion matrix, from which accuracy, precision, and F-score can be calculated, as presented in Table 2, we have implemented ResNet 18 as Transform learning. The batch sizes were set to 32, 100 iterations and 0.0003 learning rate for this proposed model. The evaluation of the suggested model's performance involves an analysis based on essential metrics, including "classification accuracy," "F-score," "Precision," "confusion matrix," and "Recall." The process for calculating the values of these performance metrics is outlined below:

$$\text{"Precision"}=\frac{N(TP)}{N(TP)+N(FP)} \tag{1}$$

$$\text{"Recall"}=\frac{N(TP)}{N(TP)+N(FN)} \tag{2}$$

$$\text{"F-score"}=2\times\frac{precission*recall}{precission+recall} \tag{3}$$

$$\text{"Accuracy"}=\frac{N(TP)+N(TN)}{N(TP)+N(TN)+N(FP)+N(FN)} \tag{4}$$

Details are presented regarding the cumulative true positives denoted as N(TP), cumulative false positives denoted as N(FP), cumulative true negatives denoted as N(TN), and cumulative false negatives denoted as N(FN). These metrics are individually calculated for each class. To assess the overall performance of the algorithm, the average of these metrics across the two classes is taken into account.

Confusion retinopathy Matrix:

Table 1: Confusion Matrix of the Proposed Algorithm

True Class	Predicted	
	Abnormal	Normal
Abnormal	140	8
Normal	7	110

Table 2: Performance Analysis of the Proposed Algorithm for Detecting and Classifying Diabetic Edema

Class	Precision	Recall	$F1_{score}$	Support
Abnormal	0.95	0.95	0.95	148
Normal	0.93	0.94	0.94	117
Average	0.94	0.94	0.94	265

Table 2: External validation for Detection and Classification OfDiabetic Edema

Author	DataSet	Classification Model	Accuracy(%)
CNN, Xu et al.(2017)	Kaggel	CNN	94.5
Usman et al.(2023)	Dataset	ResNet 152	94.4
Alyoubiet al.(2020)	Dataset	Resnet 3	85
Li, Xiaomenget al.(2019)	IDRiD	ResNet 50	92.6
Proposed	Messidor-2	Improved ResNet 18	95.1

The following Figures are description of the accuracy of the analyzed performance:

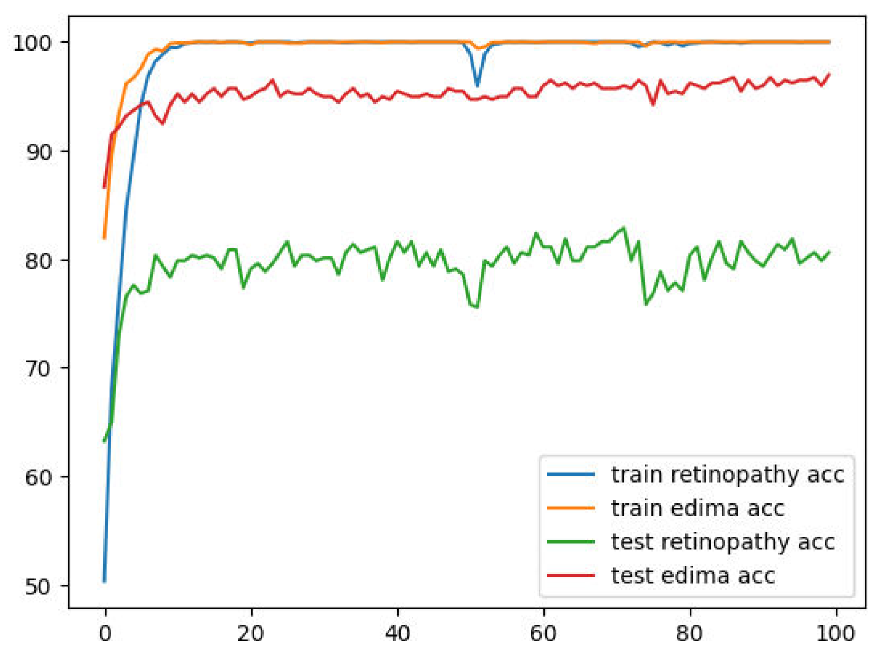

Figure: 9 Accuracy graph of Retinopathy and Edema

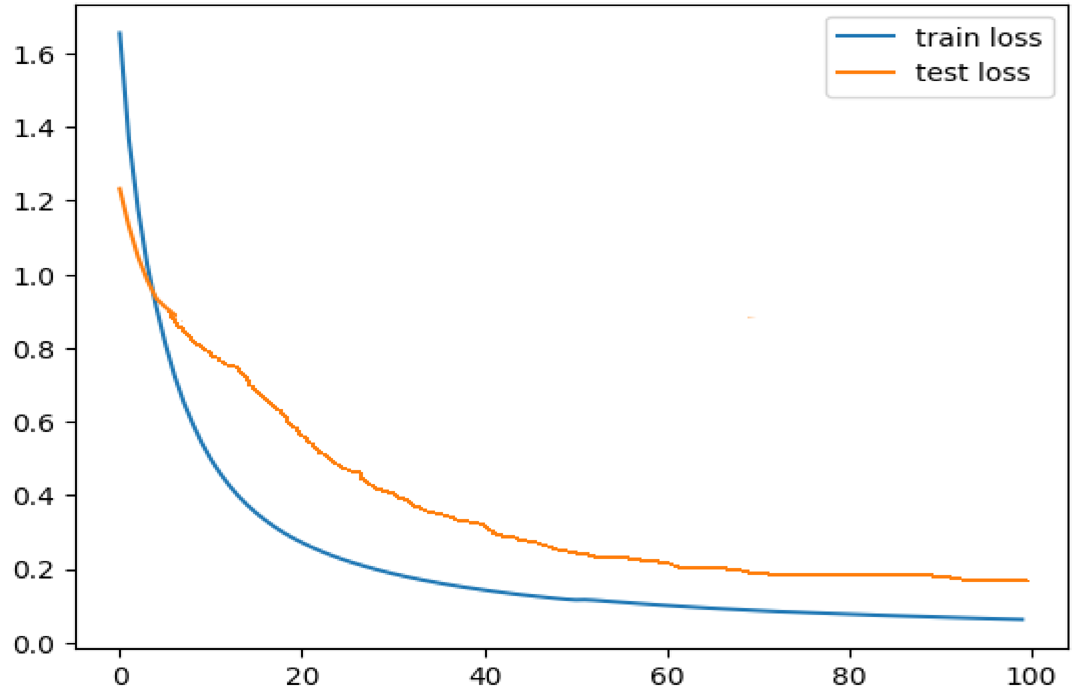

Figure: 10 Representing train and test loss

Conclusion:

The incorporation of Internet of Things (IoT) technologies in diabetic retinopathy management offers a promising approach to improving patient care and outcomes. By leveraging IoT devices such as retinal imaging systems and wearable sensors, healthcare providers can facilitate early detection, monitoring, and timely intervention for diabetic retinopathy. Furthermore,issues like data security, privacy concerns, and interoperability challenges must be carefully addressed to ensure the successful implementation and integration of IoT solutions in diabetic retinopathy care. Collaboration among healthcare providers, technology developers, regulatory agencies, and patients is crucial to overcoming these challenges and fully harnessing the potential of IoT to enhance the management of diabetic retinopathy. Overall, the integration of IoT and diabetic retinopathy holds great promise for advancing the quality and accessibility of eye care for individuals living with diabetes.

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