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A COMPARISON OF TEXTURE-BASED DIABETIC RETINOPATHY CLASSIFICATION USING DIVERSE FUNDUS IMAGE COLOR MODELS

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Abstract. *Diabetic retinopathy is the first major complication of diabetes that is the leading cause of blindness. An eye abnormality screening procedure requires the expertise of ophthalmologists in examining fundus images. Accurate classification of the disease's severity and stage will reduce the disease progression rate. The automatic DR classification is essential for diagnostic assistance by ophthalmologists. A comparison-based DR classification utilizing texture features over different color spaces is proposed in this paper. These approaches were evaluated using the DR public dataset Kaggle by reclassifying five severe stages of the disease as normal and abnormal. Non-Local Means Denoising (NLMD) and Contrast Limited Adaptive Histogram Equalization (CLAHE) are implemented on the image dimensions and resolution to improve image quality and optimize computational efficiency. Following the preprocessing of the RGB images, three color models, namely HSV, LAB, and YCrCb, are derived prior to the extraction of the texture features. Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) features are depicted as input data to generate texture-based features from four different color models. We conduct straightforward comparative evaluations to identify an appropriate solution DR classification technique, which includes Logistic Regression (LR), Decision Tree (DT), and Support Vector Machine (SVM). The performance of conventional classification models is noteworthy, as indicated by the LR model achieving an accuracy rate of 82% on both the LBP and GLCM features. It is possible to implement the DR prior screening system utilizing the optimal model. This study suggests that in order to facilitate the implementation of clinical applications, it may be beneficial to propose lesion segmentation for identification in order to promote higher precision in DR classification.*

Keywords: Texture feature, Color models, Diabetic retinopathy classification, Retinal fundus image, Texture-based classification, Machine learning

1. **Introduction.** Globally, Diabetic Retinopathy (DR) is the leading cause of blindness and vision loss. Blood vessels in the retina can develop improperly illustrated in Figure 1 [1]. Early detection and classification are required to prevent and treat DR. Clinical

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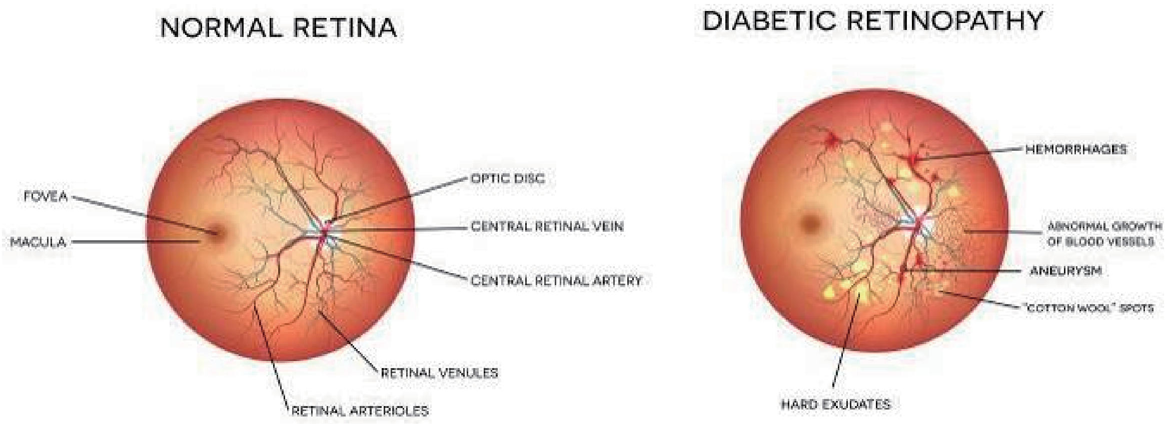

Figure 1. Normal retina vs. diabetic retinopathy characteristics [1]

application of automatic DR classification is challenging. Retinal images are frequently used in pre-training datasets for classification models. The feature of DR is essential because DR symptoms mostly appear based on the vascularized features.

A recent study has developed and evaluated methods for the automatic categorization of DR. Conventional and texture characteristics are still relevant for DR classification. In order to identify and address DR research difficulties, [2] examined DR detection methods, retinal datasets, and performance measurements. Several techniques have been applied to classifying DR. These methods have demonstrated cutting-edge performance on publicly accessible datasets, indicating their clinical application. Despite this, recent studies have demonstrated the efficacy of feature-based classification approaches in diagnosing DR by employing traditional machine learning algorithms with lower computational complexity. Therefore, feature extraction, classification, and regression techniques were challenged and proposed to be used to discriminate DR.

By identifying the most capabilities, algorithmic feature selection can enhance these methods. Classification of DR using the abovementioned techniques may be sensitive to diseases such as white or yellow lesions, exudates, or bright artifacts on retinal imaging [3]. The texture is crucial to human visual and well-defined DR features (abnormal blood vessels, exudates, microaneurysms, and hemorrhages). Considering the spatial relationship of pixels, the Gray Level Co-occurrence Matrix (GLCM), some statistics further describe the texture (i.e., contrast, correlation, energy, entropy, and homogeneity). GLCM is essential in analyzing medical imaging [4,5]. It can also be used to classify diabetic retinopathy. Different lesions were studied in [6] by evaluating texture features using GLCM for training with pattern recognition classification challenges to obtain maximum precision. Several empirical studies demonstrate that the Local Binary Patterns (LBP) operator has also been modified to provide a good image texture measure with exceptional precision and computing complexity. Each image patch is segmented and processed to generate LBPs with homogeneous characteristics. Even though texture feature-based identification approaches provide an acceptable level of accuracy, there are still issues in the experiment, and the identification accuracy must be improved and initiated.

Furthermore, the most significant visual feature for humans is color, determining the color of an object based on its luminance and chromaticity. Different color models also emphasize different features of DR. Color fundus imaging is more effective at detecting retinal disease [7]. Although RGB is the most generally used color space, several color spaces provide color information, and this feature facilitates precise computations and color identification. Others, however, individual specify hue (green), saturation (dark green), and luminance (intensity). Raw DR fundus images can be analyzed in a non-RGB color space, and classifying DR images investigates multiple color spaces.

The abovementioned point of view texture feature extracted from different color models is interesting to contribute to DR classification challenges. Our objective in this paper is to use a machine learning model to automate the DR classification process of texture-based features over color models to which the texture-based features are compared, LBP and GLCM. The comparison of DR classification using texture features extracted from the different four-color models is also investigated. Four color models: RGB, Hue Saturation Value (HSV), LAB, and YCrCb, motivated our study. The rest of this article is organized as follows. Section 2 elaborates related research overview. Section 3 describes methodology followed by evaluation and results and discussion in Section 4. Finally, conclusions and future works are given in Section 5.

2. **Related Research Overview.** Previous studies of the DR classification system, which served as a basis for essential experiments, developed more effective current research. Automated DR detection has been studied to assist ophthalmologists with screening prior to intensive medical care. By obtaining the most capabilities, algorithmic feature selection can enhance DR classification methods. We mainly compare DR classification using texture features extracted from the different color models. This review will examine recent work in DR classification using feature-based classification techniques, which will be separated into conventional and texture-based image features.

2.1. **Review on feature-based DR classification.** Blood vessel segmentation, microaneurysm identification, hemorrhage detection, exudate detection, and optic disc and optic cup segmentation approaches are among the most frequently examined retinal features for DR detection and lesion segmentation. Several approaches have been applied to the classification of DR to detect the retinal features. Mateen et al. [2] comprehensively investigated DR identification and segmentation techniques. In DR, medical biomarkers have also been investigated. Bilal et al. [8] combined models to make the DR detection approach more reliable using SVM, KNN, and Binary Trees (BT) classifiers. Transferring the pre-processed image to the bright and red lesion detection algorithms allows feature extraction on the detected regions using morphological procedures and the adaptive threshold to extract bright regions and red lesion segmentation. Texture features also identify diabetic retinopathy. Sahoo [9] examined and implemented methods for obtaining these features from digital fundus images. Based on GLCM, these pixel intensity values calculate entropy, contrast, and correlation as texture features. Following the preprocessing step, the GLCM features extraction technique was used to extract the textural features of the segmented binary images [10] separately to grade exudates (bright regions) and microaneurysms (red regions). The green channel shows the most contrast between the DR features. In order to determine DR features, detection features such as intensity, gray levels, color, contrast, and shape were used [11]. However, it is limited as it only provides a few visible DR features for feature extraction on green channel fundus images. Extraction of features from numerous color models is an interesting area of study.

2.2. **Review on DR classification using machine learning.** DR is classified into two types [12]: nonproliferative DR (NPDR) and proliferative DR. Regarding NPDR anomalies, they are classified as mild NPDR, moderate NPDR, severe NPDR, and very severe NPDR. Researchers attempted to determine the disease's severity and stage accurately. Sarhan et al. [13] studied machine learning strategies for identifying eye diseases during a four-year period (2015-2020). It discusses the use of machine learning to segment the retina's blood vessels, layers, and fluids. Most Machine Learning (ML) algorithms for detecting diabetic retinopathy are developed separately. Pragathi and Rao [14] proposed an effective integrated ML technique based on Support Vector Machine (SVM), Principal Component Analysis (PCA), and Moth-flame optimization. SVM outperforms with a performance of 76.96%. All ML methods are implemented after PCA decreases the dimensionality of the dataset. When combined with PCA, Naïve Bayes (NB), Random Forests (RF), and SVM perform much worse, whereas Decision Tree (DT) performs significantly better.

3. **Methodology.** Our objective is to automate the process of DR classification using machine learning with the help of color and texture features, which has five stages illustrated in Figure 2. Cropped and augmented RGB images are used as input data in the data collection stage. Non-Local Means Denoising (NLMD) and Contrast Limited Adaptive Histogram Equalization were applied for the preprocessing stage to eliminate noise and improve image quality. The preprocessing RGB images are then converted to three color spaces to construct color features. In the feature extraction stage, three color spaces and RGB color space were extracted from two texture features: GLCM and LBP. The feature dimension derived from GLCM and LBP is around 24 dimensions per algorithm, which is quite large. Classification models are suitable for partitioning high dimensions such as SVM, Logistic Regression, and Decision Trees. SVM has a kernel function that helps classify ambiguous data efficiently. Logistic Regression (LR) has a low chance of overfitting, and this method is easy to train, while DT results in a trained model that is easily interpretable. Therefore, the final stage is DR classification based on LBP and GLCM features extracted from the four-color models by the classification models: SVM, LR and DT.

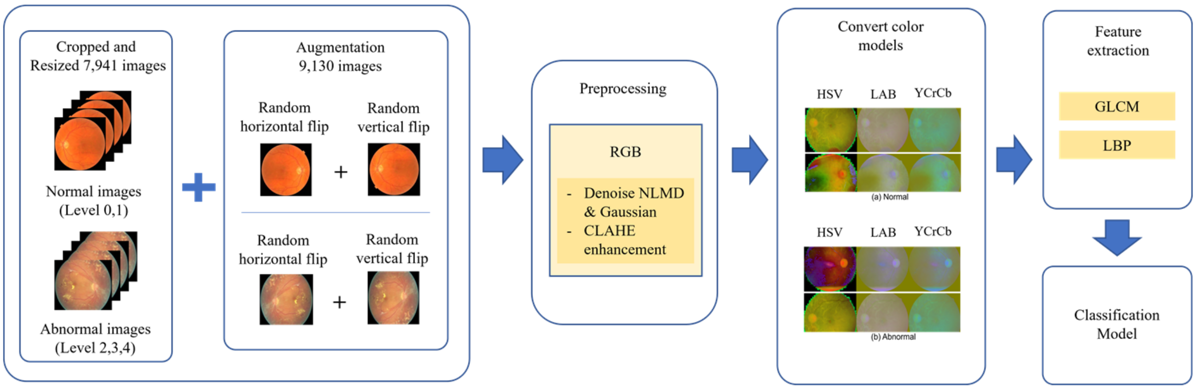

Figure 2. Proposed method

3.1. **Data collection.** For experimentation, we used 9,130 fundus images from a public dataset, Kaggle [15]. The dataset consists of high-resolution fundus images graded by trained professionals. The images were first preprocessed to improve image quality and eliminate noise using NLMD and CLAHE techniques. While preparing data for training and testing, we divided the dataset as normal (6,391 images) and abnormal (2,739 images) and resized these images to 512 $\times$ 512 pixels. DR stages I and II are considered clinically normal while all three stages III, IV, and V are abnormal. Among the 7,941 cropped and resized images from Train001, there are 6,391 normal and 1,550 abnormal images. The abnormal dataset required data augmentation to maintain the balance for classification, which required scaling normal : abnormal to 70 : 30, with a total of 2,739 abnormal images after random horizontal and vertical flipping (augmented for 1,189 images).

3.2. **Image preprocessing.** The images were then preprocessed to improve image quality by eliminating noise and improving illumination contrast using NLMD and CLAHE techniques. In image enhancement, smoothing techniques such as Gaussian and Median filtering eliminated noise, and noise removal was a neighborhood operation. Using window patches, for each pixel, the average of all windows was determined, and the pixel was replaced, so-called the non-local means denoising. This research required four parameter settings: templateWindowSize, searchWindowSize, h, and hColor, which were set to 10, 10, 7, and 21, respectively. We then equalize the denoised images using CLAHE, a form of Adaptive Histogram Equalization (AHE) to prevent unfairly gaining contrast. CLAHE operates on a tile-sized region of the image to strengthen image contrast. This study required two CLAHE parameter settings: clipLimit and tileGridSize, which were set to 0.005 and 8×8 pixels, respectively. The preprocessed images investigated in this study are shown below in Figure 3.

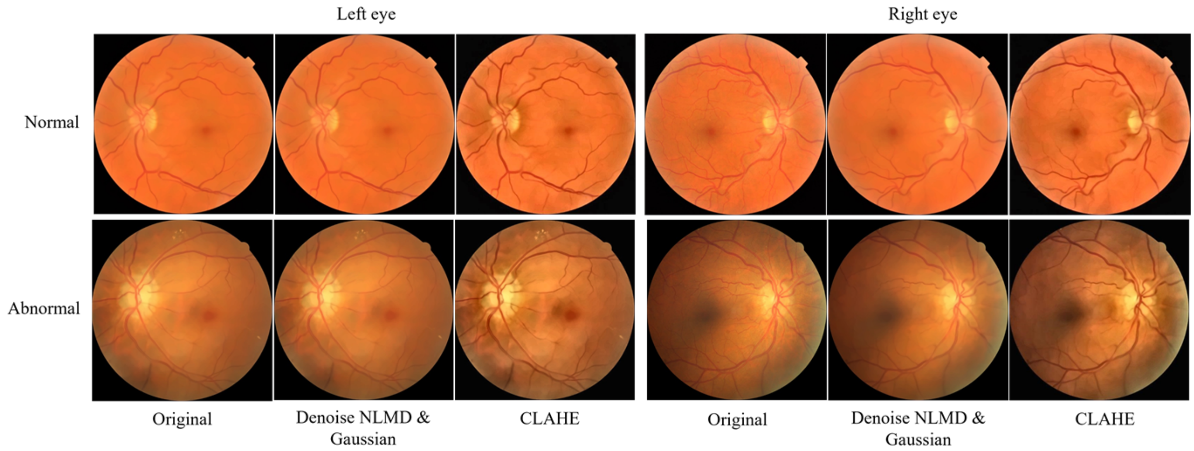

FIGURE 3. Preprocessed images

3.3. **Convert color models.** The most significant visual feature for humans is color. When looking at a color object, the human optical system may perceive and characterize it based on its luminance and chromaticity. Chromatic features define the physical nature of the lesion [16]. Although RGB is the most generally used color space, several color spaces are available because they provide color information differently. This facilitates precise computations more convenient and provides a way to identify more intuitive colors. Dissimilar color space rather than RGB could inspect raw DR fundus images. Several colour spaces are examined through the classification of DR images [17,18]. Our study investigates four color models: RGB, HSV, LAB, and YCrCb.

3.4. **Feature extraction.** In this step, feature extraction is taken from four color image channels to extract the texture feature using GLCM and LBP techniques to compare the distinctive features of these algorithms. **GLCM** is an algorithm used to identify the critical characteristics of an object or area of interest in an image based on texture analysis principles. Whether it is analyzing the intensity or gray level of an image or different dimensions of color, a standard indicator matrix can measure the texture characteristics of an image. This generated texture feature determination is often called the Haralick feature [19]. Considering the spatial relationship of pixels, GLCMs are generated by calculating the frequencies at which pairs of pixels with specific values and at a specified spatial relationship occur in the image. **LBP**, an efficient texture operator, labels the image pixels by surrounding pixels thresholding and expressing them in binary numbers [20]. The LBP operator is a grayscale-invariant texture measure derived from a description of a neighborhood's texture. Each image patch is segmented and processed to generate LBPs with homogeneous characteristics. Figure 4 illustrates the GLCM and LBP features over color models. The parameters of GLCM are levels, kernel_size, distance, and angle set to 8, 5, 1.0, and 0.0, respectively, while the parameters of LBP are numPoints, radius, and method defined respectively to 24, 3, and "uniform".

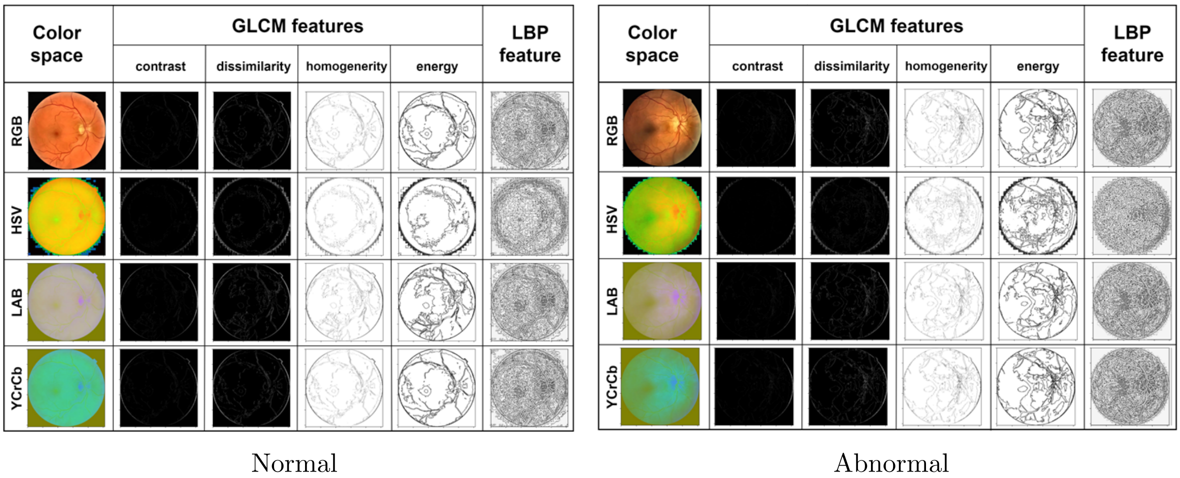

FIGURE 4. Texture features over color models

3.5. **Texture feature-based DR classification using machine learning.** The classification models were constructed using Decision Tree (DT), Support Vector Machine (SVM), and Logistic Regression (LR) classifiers. **DT** is a visual representation of the different scenarios of a set of related possibilities represented mathematical model that simulates human decisions. It considers object characteristics and uses decision trees to create predictive models that link observation data to destination data. A general decision tree consists of a single root node, internal and leaf nodes, and branches. The leaf nodes indicate the class to be given to a sample. Each internal node of a tree corresponds to a feature, and branches indicate feature conjunctions that result in data classification. The **SVM** intends to separate the hyperplane two classes by the maximum possible margin. A hard margin can be utilized when classes are entirely linearly separable. Otherwise, a soft margin is required. This algorithm was proposed by Cortes and Vapnik [21] to minimize prediction errors. Using a mapping function, it tries to create the optimal separating hyperplane between the segments. The SVM utilized in this study was implemented linearly with LibSVM to process DR detection capabilities using the training dataset. **LR**, one of the supervised machine learning algorithms, is a multivariate analysis technique whose objective is to estimate or predict whether events of interest will occur under the influence of factors. It is commonly used with binary classification problems, which predict the discrete output variable.

4. **Evaluation and Results.** The evaluation methods and the experimental results of this research are described in this section.

4.1. **Evaluation.** In retinal images, algorithms are evaluated by measuring the two types of classification accuracy of medical data that exist (disease and not disease). In medical research, digital fundus images, primarily of diabetic retinopathy, the precise DR stage grading has been examined to evaluate DR classification performance. Accuracy, precision, and recall are depicted to yield numerical results. Accuracy quantifies the reliability measures where the stability obtained by repeated tests is under the same conditions. A recall is the ratio of correctly classified images to total positive classifications, and precision is the ratio of true positives to total predicted positives.

4.2. **Results and discussions.** This section compares the DR classification based on LBP and GLCM features extracted from the four-color models. Table 1 depicts the experimented results differentiated by the decision tree, SVM, and logistic regression classification models. The LBP feature classification result gave an average accuracy of 0.75, which was greater than the average classification using GLCM of 0.68. The classification

Table 1. Experimented results

Color models	**Machine learning model**	**LBP feature**			**GLCM feature**		
		Accuracy	***Precision***	***Recall***	***Accuracy***	***Precision***	***Recall***
RGB	Decision tree	0.72	0.81	0.78	0.65	**0.75**	0.75
	SVM	0.82	0.80	0.98	0.70	0.70	1.0
	Logistic regression	**0.82**	**0.81**	0.96	0.70	0.70	0.98
HSV	Decision tree	0.69	0.78	0.78	0.62	0.73	0.72
	SVM	0.77	0.77	0.97	0.70	0.70	1.0
	Logistic regression	0.78	0.78	0.95	**0.70**	0.70	0.99
LAB	Decision tree	0.70	0.78	0.79	0.64	0.74	0.73
	SVM	0.70	0.70	1.0	0.70	0.70	1.0
	Logistic regression	0.80	0.79	0.96	0.70	0.70	1.0
YCrCb	Decision tree	0.69	0.78	0.79	0.63	0.73	0.74
	SVM	0.72	0.72	1.0	0.70	0.70	1.0
	Logistic regression	0.79	0.79	0.95	0.69	0.70	0.98

results of the LBP feature from three classifiers, LR, SVM, and DT, gave average values of 0.80, 0.75, and 0.7, respectively. While GLCM features classified by three classifiers, LR, SVM, and DT, gave average values of 0.70, 0.70, and 0.64, respectively. Considering feature extraction based on RGB color provides better accuracy on average than other color spaces using three classifiers at 0.79. However, the highest classification result derives from feature extraction on RGB with LBP feature using logistic regression classifier at 0.82.

From our experiment, LR applied on the LBP feature yielded the highest accuracy. LBP feature, a powerful texture classification performance and robust to diverse illuminations, separates fundus images on RGB into normal and abnormal categories better than using the GLCM feature when classifying with LR algorithms. The limitation of the study is working on low-quality images, and the machine learning models returned lower accuracy from numerical data than expected. Thus, the following recommendations can improve CAD-assisted DR identification: 1) Collect numerous high-resolution images from various societies; 2) Use hand-engineered and non-hand-engineered additional features to enhance categorization, particularly at extreme DR levels. Utilize novel color appearance and space classification methods to classify challenging patterns. Diabetic Macular Edema (DME), the leading cause of blindness among people with diabetes, must be monitored [2].

Classification and segmentation are the two issues discussed most frequently in these studies. Classification of eye diseases contributes to more effective screening programs, enabling healthcare organizations to serve a larger population. On the other hand, the segmentation of vessels and a retinal layer or lesions such as intra-retinal fluid may be used to improve disease detection performance or as a crucial preliminary stage of clinical decision support systems [22].

5. **Conclusions and Future Works.** The extractions of Diabetic Retinopathy (DR) features based on classification are compared. We aimed to find the model and feature giving the highest accuracy while classifying the public images as normal and abnormal by studying four color features: RGB, HSV, LAB and YCrCb. The Kaggle DR dataset is used in this study. Preprocessing and downscaling RGB images improves image quality

as well as processing efficiency. Texture features, GLCM and LBP, are investigated for constructing a classification model. Experiments involving logistic regression, decision tree, and SVM are employed to train classification models utilizing comparison data. The best experimental outcomes was the logistic regression model on the LBP feature, which had an accuracy of 82%. Logistic regression is also helpful in GLCM. The probability that an abnormal test result reveals DR is represented by a positive predictive value (precision).

Consequently, image-based feature extraction and preprocessing are still crucial. Several research is suggested for DR classification refinement. The Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architectures are integrated, where the CNN layers capture the distinctive features of the input data, and the LSTM layers make predictions based on sequences. CNNs and LSTMs were developed to address challenges in detecting visual time series and extracting textual descriptions from sequences of images. A clarification is provided to overcome challenges associated with describing a single image. In the future, we aim to utilize non-image features recommended in [23] to work with the promising approaches to achieve more precise and reliable diagnosis.

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