A Survey on Digital Image Classification Features and Techniques

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Abstract- Digital image classification plays a significant role in the early detection and analysis of medical conditions. Traditionally, diagnosis is performed manually by ophthalmologists through examination of retinal fundus images. However, this process is time-consuming, requires expert knowledge, and may sometimes lead to errors due to human limitations. In contrast, automated digital image classification systems provide a faster, more consistent, and cost-effective solution by analyzing large volumes of medical images efficiently. This work focuses on the application of digital image classification techniques for identifying different stages of diabetic retinopathy. Additionally, different image preprocessing, feature extraction, and classification methods are discussed. The study also summarizes the key image features commonly used in previous research for accurate classification of retinal images into different disease categories.

Keywords- Medical image diagnosis, Frequency Feature, Clustering, DIP.

I. INTRODUCTION

There have been dramatic increase in the number of medical images which are taken for treatment planning, diagnosis, and other clinical purposes [1]. In the current clinical standards, these measurements (annotations) from medical scans are done by expert physicians. These procedures are tedious, and prone to intra- and inter-observer errors, which can readily affect the diagnosis and treatment procedure [2]. The need for using expert-level automated methods (i.e. segmentation) and software with high efficacy, which can help and ease these tasks and resolve above mentioned problems, is essential.

Ever since the first images from inside the human body were taken using X-Rays in 1895, the field of medical imaging has progressed at a considerable rate. While traditional X-Ray imaging has stood the test of time and is still used today, it has been joined by ultrasound, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT), among others. Each of these imaging modalities fills an important and often complementary niche in clinical practice providing greater insight into the human body in both health and disease than would have ever been possible without them.

The desire for detailed images of the brain has driven much of this progress, leading to the development of the field of neuro-imaging. The modern-day clinician now has an large amount of techniques at their disposal allowing for highly detailed images of individual brain structures, as well as precise measures of brain activity and processes such as metabolism and the accumulation of proteins. As per the medical image reports of a patient experts diagnose disease. As high quality image developing devices by various techniques like X-Ray, CT-Scan, MRI, etc. [3] increases the dependency of radiologist, pathologist. As most of image interpretation done by medical experts, so to reduce their load and increase the accuracy of work by automation of image diagnosis algorithms. Most of computer vision algorithms were develop to identify the image content and classify images as per visual information reflect by X-Ray, Light, Margnet, etc. [4]. Still classification of medical images into correct class for different disease is a major issue to solve.

II. RELATED WORK

Fernando K. Malerbi et. al. in [5], Participants underwent fundus photographs using a portable retinal camera (Phelcom Eyer). The captured images were automatically analysed by deep learning algorithms RAS (retinal alteration score) and DRAS (diabetic retinopathy alteration score), consisting of convolutional neural networks trained on EyePACS datasets and fine-tuned using datasets of portable device fundus images. The ground truth was the classification of DR corresponding to adjudicated expert reading, performed by three certified ophthalmologists.

Zeru Hai et. al. [6], proposed the DRGCNN (DR Grading CNN) model. To solve the problem caused by imbalanced data distribution, our model adopts a more balanced strategy by allocating an equal number of channels to feature maps representing various DR categories. Furthermore, this paper introduce a CAM-EfficientNetV2-M encoder dedicated to encoding input retinal fundus images for feature vector generation.

D. R. Manjunath et. al. in [7], done feature engineering, by various sampling methods, and hyperparameter tuning, the models demonstrated strong performance across all dataset variations. Notably, the models also yielded robust results on the original imbalanced dataset, highlighting the strength of the algorithms and the impact of careful parameter optimization. Among the tested approaches, ensemble methods, particularly Voting and Stacking Classifiers, delivered superior outcomes, achieving nearly perfect evaluation metrics on oversampled data. Hyperparameter tuning further enhanced results by lowering RMSE and log loss, while improving accuracy and recall across different settings. These findings underscore the critical role of optimization in handling real-world clinical datasets, which are often imbalanced and noisy.

Al-Waisy et. al. in [8], This study introduces Skin-DeepNet, a novel deep learning-based framework designed for the automated early diagnosis and classification of skin cancer lesions from dermoscopy images. Skin-DeepNet incorporates a two-step pre-processing stage to enhance image contrast, followed by robust skin lesion segmentation using Mask R-CNN and GrabCut algorithm.

Ashfaq et al. [9] introduced a hierarchical framework for automated skin cancer detection that employs a multi-level classification process. This layered strategy allows the system to first separate benign lesions from malignant ones and then further classify cancer subtypes, leading to more accurate and interpretable diagnostic outcomes. By progressively analyzing lesion characteristics across multiple abstraction levels, the model captures subtle visual patterns that are often overlooked, thereby supporting clinicians with more informed and reliable decision-making.

Lin TL et al. [10] proposed an advanced hyperspectral imaging-based method known as the Spectrum-Aided Vision Enhancer (SAVE) to improve the visual distinction of skin lesions. The technique transforms standard RGB images into narrow-band images by integrating hyperspectral data, significantly enhancing lesion-to-tissue contrast. The study evaluates the effectiveness of this enhanced imaging approach using ten machine learning and deep learning models—including CNNs, Random Forest, YOLOv8, ResNet50, MobileNetV2, Logistic Regression, and multiple SVM variants—to accurately classify actinic keratosis (AK), basal cell carcinoma (BCC), and seborrheic keratosis (SK).

III. IMAGE FEATURES FOR CLASSIFICATION

Color Feature: Retinopathy image analysis relies heavily on color information, as the image itself is a matrix of pixel values, where each pixel encodes a specific color based on the selected image format RGB, shown in fig. 4. Color features are critical for distinguishing various regions within the retina, such as blood vessels, optic disc, and lesions. These features are widely used in tasks like image re-ranking, classification, and object detection. In retinal images, color variations can help in identifying abnormalities such as hemorrhages, micro aneurysms, and exudates. An example of color-based feature representation, especially using the HSV color model, where hue, saturation, and value components highlight different structures within the retina.

Active Contour: Active contour models, also known as snakes, are used to detect object boundaries within images through iterative deformation. This method is particularly effective in segmenting complex anatomical structures like the optic disc or pathological regions in the retina. The contour evolves over time under the influence of internal and external forces until it aligns with the true boundary of the object. In the context of retinopathy images, active contour techniques help to delineate regions of interest, such as lesions or abnormal tissue growth, based on intensity and spatial continuity. The feature extracted using this approach enhances the structural representation of the retina, as illustrated, which demonstrates an active contour-based retinal image feature.

Discrete Cosine Transform (DCT): The Discrete Cosine Transform (DCT) is widely used in image processing for feature extraction, particularly in the frequency domain. It converts the image into a sum of cosine functions at various frequencies, allowing for compact representation of image information. In retinopathy image analysis, DCT helps in reducing dimensionality while preserving essential texture and contrast features. It effectively captures variations in retinal regions that may indicate disease progression. Fig. 7 also shows the application of DCT on retinal images, where frequency-based patterns highlight critical features for classification or diagnosis.

Eadge Feature Edge detection is fundamental in identifying boundaries and structural transitions in retinal images. Objects in an image are defined not only by their color or texture but also by the lines or transitions that mark their limits—these are known as edges. Detecting these edges is crucial for outlining anatomical features such as blood vessels or lesions. Grayscale images are commonly used in edge detection processes to simplify the analysis. Several edge detection algorithms exist, such as the Sobel, Prewitt, and Canny operators. Among them, the Canny edge detection algorithm is preferred due to its accuracy and ability to detect sharp, well-defined edges. This feature plays a significant role in highlighting boundaries in retinal images, which demonstrates edge detection in a retinopathy image using the Canny algorithm.

IV. TECHNIQUES OF IMAGE CLASSIFICATION

Supervised Learning: Supervised learning is one of the most widely used paradigms in machine learning, particularly in medical image analysis. In this approach, models are trained on a labeled dataset, where the input features are paired with the correct output labels. The goal is to learn a mapping function that can generalize to unseen data and accurately predict outcomes for new instances. This approach has proven effective in classifying retinal images for Diabetic Retinopathy detection, as it enables the system to learn from expert-annotated datasets and apply learned patterns to diagnose new cases [11], [12].

Unsupervised Learning: Unsupervised learning techniques, in contrast, operate on unlabeled datasets. These algorithms aim to discover hidden patterns or groupings in the data by modeling the underlying structure or distribution, often represented as $P(X)$, where X denotes the input data. This approach is particularly useful in clustering or anomaly detection tasks within large-scale medical datasets, where manual annotation is not feasible. In DR research, unsupervised methods are used to segment retinal structures and identify lesions without prior labeling [13].

Reinforcement Learning: Reinforcement learning (RL) introduces a goal-driven framework where agents learn optimal behaviors through interactions with an environment. The agent receives rewards or penalties based on its actions, leading it to maximize long-term rewards. RL has recently been explored in medical imaging tasks such as adaptive image enhancement or sequential diagnosis planning, where the system continuously improves by learning from feedback [14].

Support Vector Machines (SVM): Support Vector Machines are supervised classifiers that aim to find the hyperplane that maximally separates classes in a high-dimensional space. Unlike linear regression, SVMs use a hinge loss function and can be extended to non-linear problems via kernel functions (e.g., radial basis function, polynomial). SVMs are particularly suited for binary classification problems and have been effectively applied to DR classification due to their robustness in high-dimensional feature spaces [15].

Probabilistic Graphical Models (PGMs): PGMs, such as Bayesian Networks and Markov Random Fields, model the conditional dependencies among variables using graph structures. These models leverage probabilistic inference to make predictions, which is especially useful in medical domains where uncertainty is inherent. In the context of DR, PGMs help in modeling complex relationships among various retinal features and disease stages [16].

Decision Tree-Based Models: Decision trees are hierarchical models that split data into branches based on feature thresholds, ultimately leading to a prediction at the leaf nodes. Advanced ensemble versions, such as Random Forests and Gradient

Boosting Machines, combine multiple weak learners to form a strong predictive model. These models are widely used for medical diagnosis due to their interpretability and high accuracy. In DR detection, they are employed to evaluate multiple image features such as color, texture, and shape in a hierarchical manner [17].

V. CONCLUSION

This paper has brief the various approaches of adopt by researcher to classify the digital images. It was found that most of scholars has adopt machine learning models for the image classification. It was observed that researcher pre-process image to extract features. In digital image classification both spatial and frequency features were used for the training and testing. Feature optimization was done by genetic approach with standard filters. In future scholar can apply the techniques in medical image diagnosis and other important area which directly reduces the work load.

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