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DIAGNOSIS PREDICTION IN MEDICAL IMAGING: A COMPARATIVE ANALYSIS OF CLASSIFIERS

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ABSTRACT
Medical imaging is vital for diagnosing diseases and guiding treatment across specialties like radiology, oncology, cardiology, and neurology. Advances in machine learning (ML) and artificial intelligence offer opportunities to enhance diagnosis prediction from imaging data (e.g., X-rays, MRIs, CT scans, ultrasounds). This project focuses on a comparative analysis of ML classifiers for accurate diagnosis prediction, aiming to improve efficiency, consistency, and patient outcomes in healthcare. Traditional diagnosis relies on radiologists' expertise, which, while effective, can be time-consuming, subjective, and limited in leveraging all image information. This project addresses challenges like noise, variable image quality, class imbalance, and robust feature extraction by developing and evaluating ML classifiers, such as Logistic Regression and Extra Trees. Feature engineering will extract relevant image data, while model optimization and ensemble methods will enhance performance. The comparative analysis will use metrics like accuracy, sensitivity, and specificity to identify the most effective classifier. The motivation is to augment medical professionals' capabilities with quantitative, ML-driven insights, enabling faster and more accurate diagnoses. This can optimize resource allocation and improve patient outcomes. By systematically evaluating classifiers and addressing imaging challenges, this project aims to advance diagnostic tools, making them more reliable and scalable across medical specialties. The findings could transform healthcare by integrating AI into routine diagnostic workflows, ultimately supporting clinicians in delivering precise, timely, and data-driven care.

1.INTRODUCTION

Medical imaging has undergone remarkable advancements over the years, revolutionizing the way diseases and conditions are diagnosed and treated. The journey of medical imaging can be traced back to the late 19th century with the discovery of X-rays by Wilhelm Conrad Roentgen in 1895. This groundbreaking discovery paved the way for a plethora of imaging modalities, including MRI, CT scans, ultrasound, and more, each offering unique insights into the human body. Throughout the 20th century, medical imaging technologies continued to evolve rapidly, driven by advancements in physics, engineering, and computer science. The development of computerized tomography (CT) in the 1970s enabled detailed cross-sectional imaging of the body, revolutionizing diagnostic capabilities. Magnetic resonance imaging (MRI), introduced in the 1980s, provided unparalleled soft tissue contrast and became indispensable in various medical specialties. As computing power surged in the late 20th century and early 21st century, coupled with the rise of machine learning and artificial intelligence, the integration of these technologies into medical imaging became increasingly feasible. Researchers and practitioners recognized the potential of machine learning algorithms to analyze vast amounts of imaging data, extract meaningful patterns, and assist in diagnosis and treatment planning.

2.LITERATURE SURVEY

Studies have been conducted on dental and oral problems, such as gingivitis, oral cancer, mouth cancer, dental caries, dental fluorosis, periodontitis, tooth damage, dental calculus, plaque, and tooth loss. Researchers recommended adopting MASK R-CNN methods for oral disease diagnosis using their dataset [1]. SqueezeNet (carious, hypo mineralized) was also proposed for detecting anomalies like white spots, fluorescence, and others. The accuracy was 87% [2] on 2781 annotated teeth.

Dental periapical radiographs are indicated for a variety of disorders, including caries, the auditory brainstem response, and infusion-related responses [3]. This article uses panoramic dental X-rays to show how periodontitis can be automatically staged using a deep-learning hybrid approach. Using deep learning, the radiographic bone level (or CEJ level) was identified in 360-degree images of the entire hand. A unique hybrid framework was hypothesized to be able to automatically detect and categorize periodontal bone loss in each tooth. This situation calls for the use of both traditional CAD processing and deep learning for detection [4].

Dental pathologies include radicular cysts, nasopalatine duct cysts, dentigerous cysts, odontogenic kera tocysts, ameloblastomas, glandular odontogenic cysts, myxomas myxo fibromas, and adenomatoid odontogenic tumours can be identified with the help of a deep learning approach, as described in [5]. Using the periapical radiography dataset, molar and premolar detection (caries, restorative crowns) were suggested [6] using a deep CNN technique implemented in the Keras framework in Python. After training on a dataset, the authors constructed the proposed model to attain 91% accuracy. A faster R-CNN approach was developed to recognize teeth, such as upper right, upper left, lower left, and lower right, with an accuracy of 91% using self-generated dental X-ray pictures [7]. The overall accuracy of this approach was 82.8%.

The intraoral imaging data set was also made available, separating participants into those with and without inflammation. Models for both tooth recognition and inflammation detection were developed using ResNet-50. In a study [8] that compared 305 inflammatory photos to 499 non-inflammatory images, the accuracy of an inflammation recognition model was 77.12%. Dental restorations in panoramic X-rays were classified by Abdalla-Aslan et al. [9] using the Cubic Support Vector Machine (SVM) method. Differentiating between amalgam fillings (AF), composite fillings (CF), crowns (CRW), dental implants (DI), root canal treatments (RCT), and cores (CO) was successful 93.6% of the time, according to the study. The information in Table 1 allows us to draw the following conclusion.

3. PROPOSED METHODOLOGY

This research focuses on diagnosis prediction in medical imaging through a comparative analysis of classifiers, specifically Logistic Regression and the Extra Trees Classifier. It begins by importing essential libraries for image processing, data manipulation, machine learning, and evaluation.

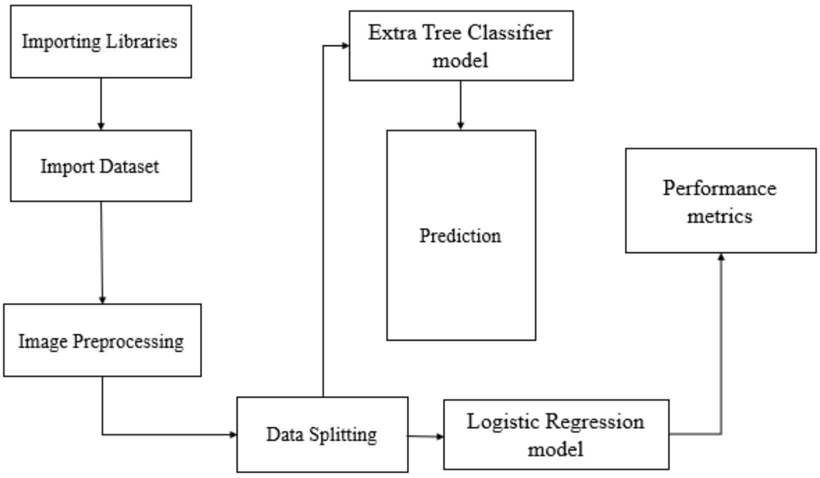

Fig.1: Block Diagram of Proposed System.

The code loads and preprocesses image data from a specified directory, including resizing, flattening, and saving processed arrays for efficiency. The dataset is then split into training and testing sets. If pre-trained models are unavailable, the classifiers are trained on the training data, and their performance is evaluated on the test set using metrics such as accuracy, precision, recall, and F1-score. The Extra Trees Classifier is further used to predict the diagnosis of a sample image, with the predicted class displayed alongside the image. Finally, confusion matrices are generated and visualized for both classifiers, offering deeper insights into their classification performance across different diagnostic categories.

3.1 Image preprocessing

Image preprocessing is a critical step in computer vision and image analysis tasks. It involves a series of operations to prepare raw images for further processing by algorithms or neural networks. Here's an explanation of each step in image preprocessing:

Step 1. Image Read: The first step in image preprocessing is reading the raw image from a source, typically a file on disk. Images can be in various formats, such as JPEG, PNG, BMP, or others. Image reading is performed using libraries or functions specific to the chosen programming environment or framework. The result of this step is a digital representation of the image that can be manipulated programmatically.

Step 2. Image Resize: Image resize is a common preprocessing step, especially when working with machine learning models or deep neural networks. It involves changing the dimensions (width and height) of the image. Resizing can be necessary for several reasons:

- Ensuring uniform input size: Many machine learning models, especially convolutional neural networks (CNNs), require input images to have the same dimensions. Resizing allows you to standardize input sizes.
- Reducing computational complexity: Smaller images require fewer computations, which can be beneficial for faster training and inference.
- Managing memory constraints: In some cases, images need to be resized to fit within available memory constraints.

When resizing, it's essential to maintain the aspect ratio to prevent image distortion. Typically, libraries like OpenCV or Pillow provide convenient functions for resizing images.

Step 3. Image to Array: In this step, the image is converted into a numerical representation in the form of a multidimensional array or tensor. Each pixel in the image corresponds to a value in the array. The array is usually structured with dimensions representing height, width, and color channels (if applicable).

For grayscale images, the array is 2D, with each element representing the intensity of a pixel. For color images, it's a 3D or 4D array, with dimensions for height, width, color channels (e.g., Red, Green, Blue), and potentially batch size (if processing multiple images simultaneously).

The conversion from an image to an array allows for numerical manipulation and analysis, making it compatible with various data processing libraries and deep learning frameworks like NumPy or TensorFlow.

Step 4. Image to Float32: Most machine learning and computer vision algorithms expect input data to be in a specific data type, often 32-bit floating-point numbers (float32). Converting the image array to float32 ensures that the pixel values can represent a wide range of intensities between 0.0 (black) and 1.0 (white) or sometimes between -1.0 and 1.0, depending on the specific normalization used.

This step is essential for maintaining consistency in data types and enabling compatibility with various machine learning frameworks and libraries. It's typically performed by dividing the pixel values by the maximum intensity value (e.g., 255 for an 8-bit image) to scale them to the [0.0, 1.0] range.

Step 5. Image to Binary: Image binarization is a process of converting a grayscale image into a binary image, where each pixel is represented by either 0 (black) or 1 (white) based on a specified threshold. Binarization is commonly used for tasks like image segmentation, where you want to separate objects from the background.

The process involves setting a threshold value, and then for each pixel in the grayscale image, if the pixel value is greater than or equal to the threshold, it is set to 1; otherwise, it is set to 0.

Binarization simplifies the image and reduces it to essential information, which can be particularly useful in applications like character recognition or object tracking, where you need to isolate regions of interest.

3.2 Extra Trees Classifier

The Extra Trees Classifier, short for Extremely Randomized Trees Classifier, is a powerful machine learning algorithm that belongs to the ensemble learning family, specifically the tree-based methods. It is an extension of the Random Forest algorithm and shares some similarities with it, but it introduces additional randomness in the tree-building process. In this detailed explanation, we'll delve into the inner workings of the Extra Trees Classifier, exploring its key components, algorithmic steps, and advantages.

Introduction to Ensemble Learning and Decision Trees:

Before diving into the specifics of the Extra Trees Classifier, it's essential to understand the concept of ensemble learning and decision trees.

Ensemble Learning: Ensemble learning involves combining multiple base learners (weak learners) to build a more robust and accurate predictive model. The fundamental idea is that by aggregating the predictions of individual learners, the ensemble model can often outperform any of its individual components.

Decision Trees: Decision trees are a popular type of machine learning algorithm used for both classification and regression tasks. They partition the feature space into regions and make predictions by traversing the tree from the root node to the leaf nodes, where each leaf node corresponds to a class label or a numerical value.

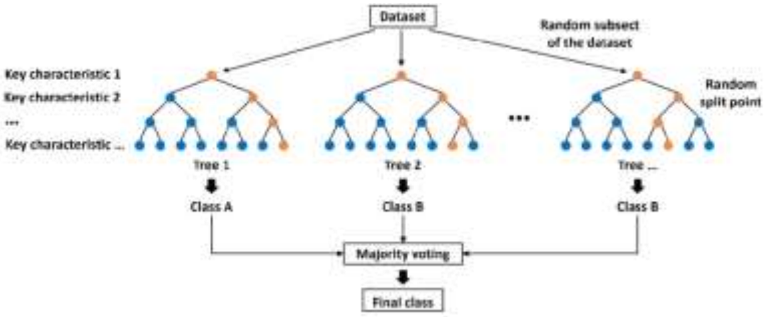

Fig. 2: Block Diagram of Extra Tree Classifier.

Random Forest and the Need for Extra Trees:

Random Forest is a widely used ensemble learning method based on decision trees. It builds multiple decision trees using bootstrapped samples of the training data and selects random subsets of features at each split point. While Random Forest is effective in reducing overfitting and improving prediction accuracy, it still involves some level of deterministic decision-making during the tree-growing process.

The Extra Trees Classifier addresses this limitation by introducing additional randomness, making it even more robust and less prone to overfitting.

4. RESULTS AND DESCRIPTION

The Dataset has different class types of mouth diseases or conditions. Here's an interpretation of the labels:

- Gum: This label represents Gingivitis, an inflammation of the gums caused by plaque buildup.
- OT: This label stands for "Other" mouth or throat conditions not specifically listed. It encompasses a range of less common or specific conditions that don't fit into the other categories listed.
- OLP: This label refers to Oral Lichen Planus, an autoimmune inflammatory disease that affects the mucous membranes in the mouth. It's characterized by white, lacy patches on the inside of the cheeks, gums, or tongue.

Fig. 3: Presents the sample dataset.

- OC: This label indicates Oral Cancer, a general term for cancer that develops in the mouth. It's a serious condition that can affect the lips, tongue, cheeks, floor of the mouth, hard and soft palate, sinuses, and throat.
- MC: This label represents Mucocele, a noncancerous mucus-filled cyst that develops on the lips, cheeks, or roof of the mouth. Mucoceles typically result from trauma to a minor salivary gland, leading to the accumulation of saliva in the tissue.
- CoS: This label stands for Chronic Sialadenitis, an inflammation of the salivary glands. It's a condition where the salivary glands become swollen and painful, often due to an infection or blockage of the ducts that carry saliva.
- CaS: This label refers to Calculi Salivary (Salivary Stones), which are mineral deposits that form in the salivary glands. These stones can cause pain and swelling in the affected gland, as well as difficulty eating or swallowing.

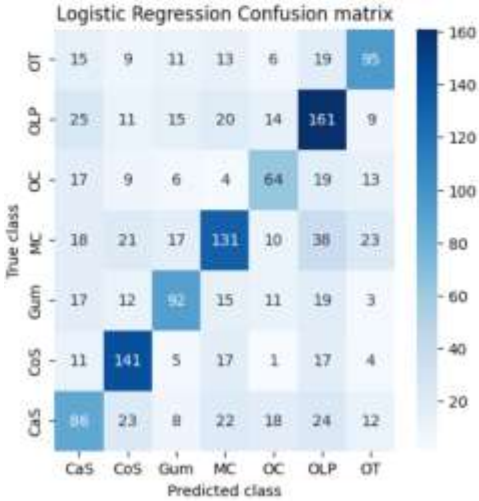

Fig. 4: Confusion matrix of logistic regression model.

Fig. 4 confusion matrix of the logistic regression model visually represents the performance of the model in classifying different categories of mouth diseases. It provides a clear overview of the true positive, true negative, false positive, and false negative predictions made by the model for each class. Fig. 5 Extra Trees Classifier model illustrates the model's performance but specifically for this classifier. It provides a visual representation of how well the model predicts the actual classes of mouth diseases, aiding in understanding its strengths and weaknesses.

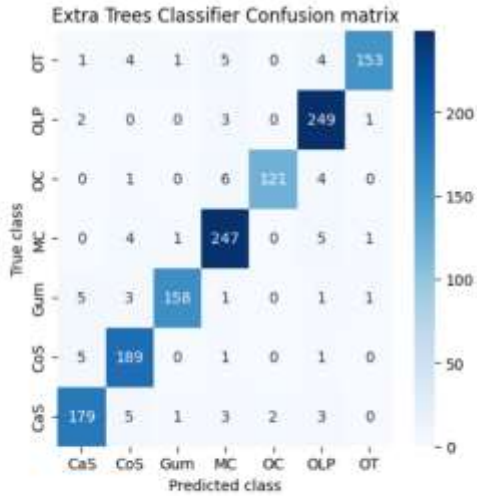

Fig. 5: Confusion matrix of Extra Tree Classifier model.

Fig. 6: Proposed ETC model Prediction of disease on test image.

Fig. 6 shows the predicted output on uploaded test image. The image classifies it as OLP. Proposed Extra Trees Classifier model's prediction of disease on a test image demonstrates the practical application of the model. By inputting an image of a mouth condition, the model predicts the corresponding disease category, showcasing its potential utility in real-world diagnostic scenarios.

5. CONCLUSION

The comparative analysis of classifiers for diagnosing various mouth diseases using medical imaging data. Both logistic regression and Extra Trees Classifier models were trained and evaluated, providing insights into their performance in accurately identifying different disease categories. The confusion matrices, classification reports, and comparison table of performance metrics highlighted the strengths and weaknesses of each classifier. Additionally, the practical application of the Extra Trees Classifier model was demonstrated through the prediction of disease on a test image, showcasing its potential utility in clinical settings.

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