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Image Processing Using Finite Element Modelling and Soft Computing Techniques – A Review

C.Sivaprakasam¹, V.K.Buvanesvari², P.Suresh³, U.Saravanakumar⁴, E.Punarselvam⁵, T.Aravind⁶

¹Associate Professor, Department of MCA, Muthayammal Engineering College (Autonomous), Namakkal,

Tamilnadu, India.

²Assistant Professor, Department of MCA, Muthayammal Engineering College (Autonomous), Namakkal,

Tamilnadu, India

³Professor, Department of Mechanical Engineering, Muthayammal Engineering College (Autonomous), Namakkal,

Tamilnadu, India

⁴Professor, Department of ECE, Muthayammal Engineering College (Autonomous), Namakkal, Tamilnadu, India

⁵Professor, Department of IT, Muthayammal Engineering College (Autonomous), Namakkal, Tamilnadu, India

⁶Assistant Professor, Department of CSE, Muthayanmal Engineering College (Autonomous), Namakkal,

Tamilnadu, India

ABSTRACT: Technology evaluation in healthcare makes disease detection and treatment more convenient. The collection and storage of data or medical records has become easier in recent years. It has been shown that machine learning algorithms and image processing techniques have fundamental potential in detecting a variety of diseases, such as cancer, pneumonia, diabetes, etc. Using image processing, doctors and patients can see internal diseases more easily, making them easier to diagnose. It is important to predict major and minor diseases in order to detect health threats at an early stage. Patients and doctors need to identify diseases like cancer, pneumonia early in order to make early treatment decisions. By using the latest technology trends, like image processing and machine learning, this task becomes easier. Machine learning and Image processing gives more accurate results than naked eye and predicts within fraction of seconds.

This proposed system is web application which will predict disease:

- ✤ Based on symptoms.
- Based on image reports (like x-ray, mammography, MRI, etc)
- * Based on given diagnosis report parameter values.
- Suggest nearby specialists based on predicted disease.

I. INTRODUCTION

Among the most common computer vision tasks in medical image applications are image classification, medical image segmentation, and detecting shapes and objects of interest. Methods based on deep learning (DL) have proved superior to traditional methods in handling such challenging tasks for cancer detection, MRI segmentation, X-ray analysis and many other medical applications.

Another rapidly growing area of research in medical imaging is Computer Aided Diagnosis (CAD). Recent research attempts have focused on improving computer-aided diagnosis systems because errors in medical diagnostics can negatively affect medical treatment. Machine learning is important in Computer Aided Diagnosis. After using an easy equation, objects such as organs may not be indicated accurately. So, pattern recognition fundamentally involves learning from examples. In the field of bio-medical, pattern recognition and machine learning promise the improved accuracy of perception and diagnosis of disease. They also promote the objectivity of decision-making process. For the analysis of high-dimensional and multimodal bio-medical data, machine learning offers a worthy approach for making classy and automatic algorithms.

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The Disease Detection module follows the following steps:

- 1. *Image Acquisition:* Image acquisition is the collection or collection procedure with and without disease. The system's accuracy depends mostly on the picture kinds utilised, as training is carried out. Images are taken from or collected using a digital camera/scanner on the infected organs. The quality of the image relies on the kind and orientation of the digital camera employed. The first procedure is to acquire the picture data that is utilised as a computational input. Image data entry in .bmp,.jpg,.png,.gif format should be provided.
- 2. *Image Pre-processing:* Pre-processing of the picture follows acquisition of the image. Image pre-processing refines images by noise, enhance, resize, increase data, cuts, convert colour space, smoothing etc. images. The recorded pictures might reveal some orientation error that are all thought to be eliminated noise. Enhanced distorted pictures with noise reduction filters that eliminate distortions. Contrast improvement techniques are required if the image contrast is poor. The job requires just sheet pictures and the rest of the pieces are regarded as the backdrop.
- 3. *Image Segmentation:* In the identification of diseases, the segmentation of picture plays an essential role, as pre-processed images are taken from the area of interest. The division of the picture into distinct portions of a infected organ X ray requires the division of the image. Segmentation may be carried out by utilizing several approaches, such as Otsu, k-means, thresholding, region, edge, etc. Deformation segmentation takes the intensity values into account when splitting photographs and this is an example of edge detection. Colour variations are seen such picture can be broken off using the clustering process k-means to remove sick parts from the healthy one.
- 4. *Feature Extraction:* The extraction procedure involves the identification and extraction of intrinsic properties known as image disease descriptive features. Colour, texture and form characteristics are generally extracted. Colour characteristics distinguish between one illness and another based on colour and are main colour aspects of the histogram and moments. For the categorization of diseases, textures that indicate how picture textures are dispersed are retrieved. Examples of textural characteristics include entropy, homogeneity and contrast. The form shows how the symptoms of the disease differ from each other. For diseases, structural extraction is better than colour and texture.
- 5. *Disease Classification:* As shown in Figure 4, the collected characteristics are utilized for the categorization of diseases. Classification is a monitored approach for mapping pictures from leaves to various disease classifications. The classifier technique produced describes the predetermined set of disease by learning from



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pictures with disease labels as shown in Figure 4. This phase of learning is known as the stage of training. The trained classifier is used to test the pictures and the precision achieved is dependent on the trained classifier.

II. EXISTING APPROACHES

a) Traditional Approach Since ancient time, in many civilizations like Indian, Chinese, Persian, Egyptian, Roman and Greek, people used to get guidance about their present and future by means of Palmistry. "Palm Reader", who is a human being used to predict attributes of human, like: health, psychology, intelligence, and lifestyle and other related entities based on his/her knowledge4.

b) Web based Approach Various web applications are being developed for palmistry. In some web applications, "Palm Reader" is required. Here it is possible that image may be degraded during file transfer. Also human perception has limitation in image resolution, object identification and color perception4.

c) Mobile Application Based Approach In case of Mobile Application based applications, sample images of palm are shown and users have to compare their own palm with the most suitable sample image. Predictions are displayed based on the selection of image by user. It is user's responsibility to identify the nearest matching image. It is difficult for user to compare the given image with his/her own palm, because every person has different set of symbols and lines on palm. If user selects wrong image, then he/she may get wrong prediction, which may be not suitable to him/her Using Image Processing and Analysis (IPAA) techniques, a system can be developed to overcome these limitation, and predict the disease/s based on medical palmistry automatically5.

III. EXPERIMENTAL METHODS

Artificial Intelligence can enable the computer to think. Computer is made much more intelligent by AI. Machine learning is the subfield of AI study. Various researchers think that without learning, intelligence cannot be developed. There are many types of Machine Learning Techniques that are shown in Figure 1.1. Supervised, Unsupervised, Semi Supervised, Reinforcement, Evolutionary Learning



Figure 13.1. Types of machine learning techniques

and Deep Learning are the types of machine learning techniques. These techniques are used to classify the data set.

1) Supervised learning: The algorithms are trained on a set of examples with suitable targets, and based on this training set, they respond correctly to any practical input. Learning from exemplars is another name of Supervised Learning. Classification and regression are the types of Supervised Learning.

Classification: It gives the prediction of Yes or No, for example, "Is this tumor cancerous?", "Does this cookie meet our quality standards?" Regression: It gives the answer of "How much" and "How many".

2) Unsupervised learning: Correct responses or targets are not provided. An unsupervised learning technique identifies similarities between input data and uses these similarities to categorize them. This is also known as density estimation. Unsupervised learning contains clustering. Clustering: it makes clusters on the basis of similarity.

3) Semi supervised learning: Semi supervised learning technique is a class of supervised learning techniques. For training purposes, unlabeled data was also used (generally a small amount of labeled data with much larger amounts of unlabeled data). Semi-supervised learning lies between unsupervised-learning (unlabeled-data) and supervised learning (labeled-data).



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4) Reinforcement learning: Algorithm informs when answer is wrong, but does not tell how to fix it. It has to explore and test various possibilities until it finds the right answer. It is also known as learning with a critic. It does not recommend improvements. The difference between reinforcement learning and supervised learning is that no accurate inputs or outputs are offered, nor are suboptimal actions clearly defined. Moreover, it focuses on on-line performance. 5) Evolutionary Learning: Biological evolution is a learning process, in which organisms are adapted to improve their survival rates and chance of having offspring. By using the idea of fitness, to check how accurate the solution is, we can use this model in a computer.

6) Deep learning: This branch of machine learning is based on set of algorithms. This algorithm uses a deep graph with multiple processing layers, including linear and nonlinear transformations.

Disease Prediction:

Disease Prediction will analyzed from training datasets through Data mining techniques:

- K-mean clustering:.The k-means algorithm is an evolutionary algorithm that gains its namefrom its method of operation. The algorithm clusters information into k groups, where k is considered as an input parameter. It then assigns each information to clusters based upon the observation's proximity to the mean of the cluster. Prophecy of heart disease using K – Means clustering techniques:
- ✤ The algorithm arbitrarily selects k points as the initial cluster centers ("means").
- Each point in the dataset is assigned to the closed cluster, based upon the Euclidean distance between each point and each cluster center.
- Each cluster center is recomputed as the average of the points in that cluster.
- Steps 2 and 3 repeat until the clusters converge. Convergence may be explained differently depending upon the performance, but it regularly explains that either no observations change clusters when steps 2 and 3 are repeated or that the changes do not make a material difference in the definition of the clusters.

IV. CLASSIFICATION OF IMAGES

4.1 Object detection

The overall objective of object detection models is to identify and localize objects. By defining which pixels within the image depict the object of interest, the localisation task determines the position of the object in the image. Identification involves recognizing objects that belong to predefined categories, or classifying objects within a bounding box. To detect initial abnormality symptoms in patients, object detection algorithms are commonly used in medical image analysis. Medical image analysis often uses object detection algorithms to detect the first signs of abnormality in patients. Generally, there are two approaches that exist in DL-based object detection models: anchor-based methods and anchor-free methods. Anchor-based methods can be divided into single-stage or multistage techniques. A singlestage technique may be faster or more computationally efficient, but it does not perform better in terms of detection performance than a multistage approach. The multistage technique has the best detection performance but is computationally costly. There are also two common single-stage techniques that are widely used as single-stage detectors with simple architectures: YOLO and SSD. To generate the final prediction map, YOLO or SSD creates a fixed number of bounding boxes and their respective scores for the appearance of objects of predefined classes within the boxes. To improve detection performance, YOLO uses a single-scale feature map while SSD uses multi-scale feature maps. In most of these methods, the bounding box or boxes containing the object/s of interest are allocated, and the final result (e.g., YOLO) is a vector containing values representing the coordinates of the center of the bounding box, its height, and width, as well as the probability it contains the class of interest.

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Figure 13.2 Schematic diagram of CNN model with arbitrary architecture

In contrast to single-stage object detection techniques, two-stage detection techniques produce a group of regions of interest (ROIs) where a complete object is likely to be found, and recognises each of them. Faster- RCNN and Mask-RCNN are commonly used examples of the two-stage detection technique. Both models first produce object proposals by a region proposal network (RPN) and then classify those produced proposals. Faster-RCNN defines the bounding box by defining the co-ordinates of the object. Mask-RCNN has an additional segmentation branch. CornerNet is one of many researchers working on anchor-free methods of object detection. Using the top-left and bottom-right corner of the object bounding box, CornerNet reduces the use of anchor boxes.

4.2 Segmentation

The concept of image segmentation refers to the process of dividing an image into areas with similar characteristics pixel by pixel. Segmenting medical images is the process of identifying a body organ or anatomical part in an image. Segmentation methods produce pixel masks for the region of interest, while object detection methods often produce bounding boxes. Applications include: segmentation of the whole heart, lung, brain tumours, skin and breast tumours. Like other CV tasks, segmentation can also be applied to different medical image modalities. Fully convolutional neural networks (FCNs) were introduced to achieve a great breakthrough in DL-based image segmentation. The U-Net model is one of the most famous end-to-end FCN models used for segmenting medical images. Litjens et al. present a detailed review of U-Net and its extensions' application to segmenting medical images.

Recent advances in DL have greatly benefited heart-related applications. An example would be right ventricle (RV) segmentation to study and detect the anatomically complex shape of the chamber, which would aid in the diagnosis of diseases directly related to the RV, such as coronary heart disease, congenital heart disease, and pulmonary hypertension. RV is one of the four chambers of the heart, along with the left ventricle (LV), right atrium (RA) and left atrium (LA). A DL-based framework was proposed by Luo *et al.* to segment the chambers of the heart from magnetic resonance images. An ensemble of DL methods based on comprehensive learning particle swarm optimization (CLPSO) was implemented in a recent study by Dang et al. to detect pulmonary hypertension. To achieve this, they trained six transfer learning models for segmentation, which were then assembled to produce the best results possible. CLPSO was used to optimize the combined weights of this output, which was calculated as the weighted sum of segmentation outputs.



Figure 13.3 Schematic diagram of object detection methods



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V. CONCLUSION AND FUTURE DIRECTION

Over the past decade, medical image analysis and understanding have made significant progress, and can be measured by orders of magnitude. Computer vision (CV) tasks such as classifying images, detecting and tracking objects in video streams, and localizing and segmenting areas of interest became relatively easy. This development can mostly be attributed to advancements in algorithms, especially convolutional neural networks-based methods, computing power improvements, and finally, the availability of large quantities of public medical images and related data. Image classification, for example, requires accurately labeled data, and ideally, this should be done by multiple medical experts to ensure minimal bias. Similarly, to build a model that is capable of tracking an object of interest, in a surgery video, enough videos and images need to be labelled and fully annotated (e.g., drawing a bounding box or a mask around the region of interest). It can be said that most of these data labelling/annotation tasks are still based on manual or semi-automated approaches. However, algorithms currently under development have the ability to work from partially annotated data and intelligently and automatically annotate images successfully.

Even if data is gathered widely and labour-intensive data annotation is carried out perfectly, there may still exist an inherent class imbalance within the data itself. Recent developments in the literature imply that there are algorithmic ways to successfully overcome this challenge, too. Future work may include building on existing data generation methods such as generative adversarial networks (GANs) to produce more diverse datasets without the need to gather and label/annotate individual samples. GANs have proven to be capable of generating realistic and diverse images from noise and provide a possible solution to generate data conditioned on a particular class of interest and solve the class imbalance problem. Another direction to consider is to develop deep learning (DL)-based methods that can learn from smaller datasets, reducing the need to label and annotate datasets at least in part.

In addition, machine learning models need to be built from the ground up with interpretability in mind. In addition to building trust among medical practitioners and patients, this will ensure that accurate, explainable DL models can be quickly deployed in the medical field. The need for ongoing collaboration between experts in the medical and AI fields is urgent. Taking this step will ensure that expert knowledge remains at the core of developing accurate, understandable, and most importantly, usable CV techniques that will advance medical care globally.

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