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Classification of X-ray Images for Human Body Parts

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ABSTRACT--*Due to advances in medical imaging technology, there is a proliferation of diagnostic images acquired in medical centres that need to be stored, analysed, retrieved and classified. The development of automatic analysis of X-ray images and classification methods is a pressing need that will have a critical impact on clinical practices by reducing human errors. Analysis of X-ray images is mostly being done by medical specialists, as it is a critical sector and people anticipate the highest level of care and service regardless of cost. Depending on just one technique to gain a high accuracy rate for every individual class is unreliable. In this paper, the classification of medical X-ray images against body parts using a pre-trained deep convolutional neural network (DCNN) and two handcrafted descriptors in a joint approach is enclosed.*

Keywords--*Body-parts classification, handcrafted features, deep features, pre-trained CNN, joint approach.*

I. INTRODUCTION

Medical imaging is a useful resource and is an invaluable tool for clinicians since it is a process where the interior of a body and its function is visually represented for analysis and intervention that seeks to reveal internal structures. Usually, the labelling of these images is performed manually and needs a lot of professional expertise, which is time-consuming, and prone to errors because of human subjectivity and variable image quality [1]. This led to the dire need for automatic medical image classification. Different sorts of medical imaging techniques such as X-ray, MRI (Magnetic Resonance Imaging), CT (Computer Tomography), Ultrasound, etc. help constrict the causes of an injury and make sure that the diagnosis is accurate. X-rays are mostwidely used amongst these techniques. Although you need more subtle tests, you are likely to get an x-ray first.

The fundamental step for X-ray image classification is to extract meaningful features. Feature selection places a key role in the resulting accuracy rate. Especially in the medical domain, there should be no chance of error. So, the accuracy of classification should be at its best. Different kinds of visual features are available which include single descriptors for colour, texture, and shape and combined descriptors. Existing image features can be categorized as handcrafted features and learned/deep features. Handcrafted features [2] are manually extracted from images using a certain predefined algorithm based on expert knowledge. Depending on the problem different handcrafted features are to be used. Local Binary Patterns (LBP), Bag of Features (BOF), Average Grey Descriptor

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(AGD), and Grey Level Co-occurrence Matrix (GLCM) are some of the examples of handcrafted features [7].Deep learned features are extracted from images using Convolutional Neural Networks (CNN) by a training procedure to fulfil a certain task. Instead of building CNN from scratch which is time-consuming, pre-trained CNN models such as VGG16, VGG19, InceptionV3, and others can be used as a feature extractor. The proposed work contributes towards an X-ray images classification using both handcrafted visual features and deep features extracted from pre-trained CNN.

II. RELATED WORK

There were manyexisting methods, where the multiple features of one category are combined i.e. either handcrafted or deep learned features.Mueen et al. [6] proposed the classification of X-ray images performed by combining global, local and pixel features in one big feature vector. To reduce the high dimensionality of the feature vector Principal Component Analysis (PCA) was used. In the first stage, Global features are extracted, where it failed to get a good accuracy rate for some classes although those classes have enough training images.In the second stage, Local level features are extracted and can distinguish better than global features for similar classes.In the third stage, Pixel level information was extracted and provided results for classes with fewer training images, which was a failure in the case of global and local features.In the final stage, all these three levels are combined into one feature vector which has a high dimension. To avoid memory and runtime problems, it was reduced by using PCA.By this approach, comparison of support vector machine (SVM) and K-nearest neighbour (KNN) classifiers have done and performance was observed, where the classification level was increased and SVM gave more accuracy in this case.InJeanne's work[7], Firstlyfeature extraction was performed where the performance of five different feature types including Average Gray Descriptor (AGD), Colour Layout Descriptor (CLD), Edge Histogram Descriptor (EHD), Gray-level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) was investigated.Local binary patterns achieved better performance values and outperformed other feature types.

Zare et al. [11] proposed an approach whereautomatic classification of medical X-ray images was performed using different feature extraction techniques such as Gray Level Co-occurrence Matrix (GLCM), Canny Edge Operator, Local Binary Pattern (LBP), pixel value as low-level image representation, and Bag of Words (BoW) as local patch-based image representation. These features have been exploited in different algorithms for classification. Performance obtained was analysed regarding the image representation techniques used and results showed that LBP and BoW outperformed the other algorithms

III. PROPOSED METHOD

3.1 Handcrafted Features

Local Binary Patterns (LBP) and Bag of Features (BoF)/Bag of Visual Words (BoVW) belong to a non-automatic feature extraction method.

3.1.1 Local Binary Patterns

Local Binary Pattern (LBP) will be used as one of the handcrafted features in this model on the grounds that the medical images are the greyscale images. Local Binary Pattern introduced by Ojala et al [3] is an efficient texture operator that labels the image pixels by thresholding the 3 x 3 neighbourhood of each pixel with the centre value and considering the result as a binary number (also known as LBP Code). The X-ray image is first divided into blocks of the same size. Then calculate the LBP code for each pixel in a block by comparing the central pixel with its 8 neighbours.If the neighbour's value is greater than the value of a central pixel, then write '1', and if the neighbour's value is less than the value of a central pixel, then write '0'. Follow this for all pixels of a block in a clockwise direction.This results in an 8-digit binary number which is then converted into the decimal, yielding a value i.e., LBP code (SeeFig. 1).For every block, compute the histogram over the output LBP array. These histograms are then concatenated into a single feature histogram as the description of the x-ray image.The feature vector can now be processed using the Support Vector Machineclassifier to classify x-ray images against body parts.

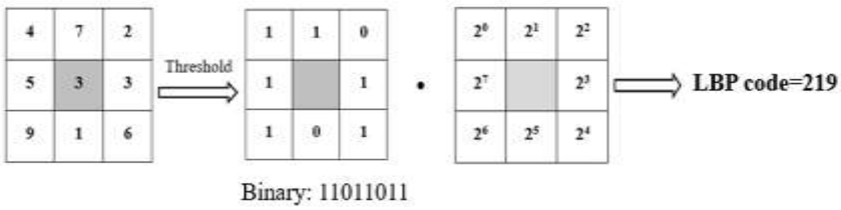

Fig.1. LBP Code Calculation

3.1.2 Bag of Features

The Bag of Features (BoF), originated from Bag of Visual Words (BoVW), is characterized as an order-less collection of image features. This method learns meaningful features and describes images in terms of the histogram of these features. Firstly, the local interest points are to be identified in an X-ray image. Scale-Invariant Feature Transform (SIFT) extracts key points and computes their descriptors. It is invariant to rotations, translations, and scaling transformations and robust to illumination variations.The features extracted are to be clustered using K-means clustering. Each feature cluster is a visual word.The final BoF vector is a histogram counting the occurrences of each visual word in the image.This feature vector can now be processed using the Support Vector Machineto classify images.

Each feature
cluster is a visual word.

3.1.3 Support Vector Machine

Support Vector Machine (SVM) is considered here since it has been one of the most successful and widely used classifiers in image classification. It is a supervised learning algorithm that looks at data and sorts it into one of the categories. Support Vector Machine has gained high performance in many medical image classification tasks [6], [14].

3.2 Deep Features

One important aspect of Convolutional Neural Networks (CNN) is that they can automatically learn hierarchical feature representations. This means that features computed by the early layersare general and can be reused in different problem domains, while features in the last layer are more dataset-specific and depend on the chosen task. Using a pre-trained Convolutional Neural Network for classification is a lot better than to build a CNN from the scratch. Here VGG-16 will be considered as the pre-trained model.

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3.2.1 VGG-16(Visual Geometry Group)

VGG-16 is one of the successful convolutional neural networks where it has a deeper architecture. It was trained on more than a million images from the ImageNet database [4]. The Keras Applications module has pre-trained deep learning models that have pre-trained weights trained on ImageNet. These models can be directly used for feature extraction as well as fine-tuning. In Fine-tuning, freeze the already trained low-level features, and only train high level features needed for our new image classification problem. Fine-tuning for this model according to the specific dataset can be performed by considering the output of the second last layer.

3.3 Combination of Deep and Handcrafted Features

Our joint approach of combining Deep and Handcrafted features for x-ray images classification is shown in Fig.2.

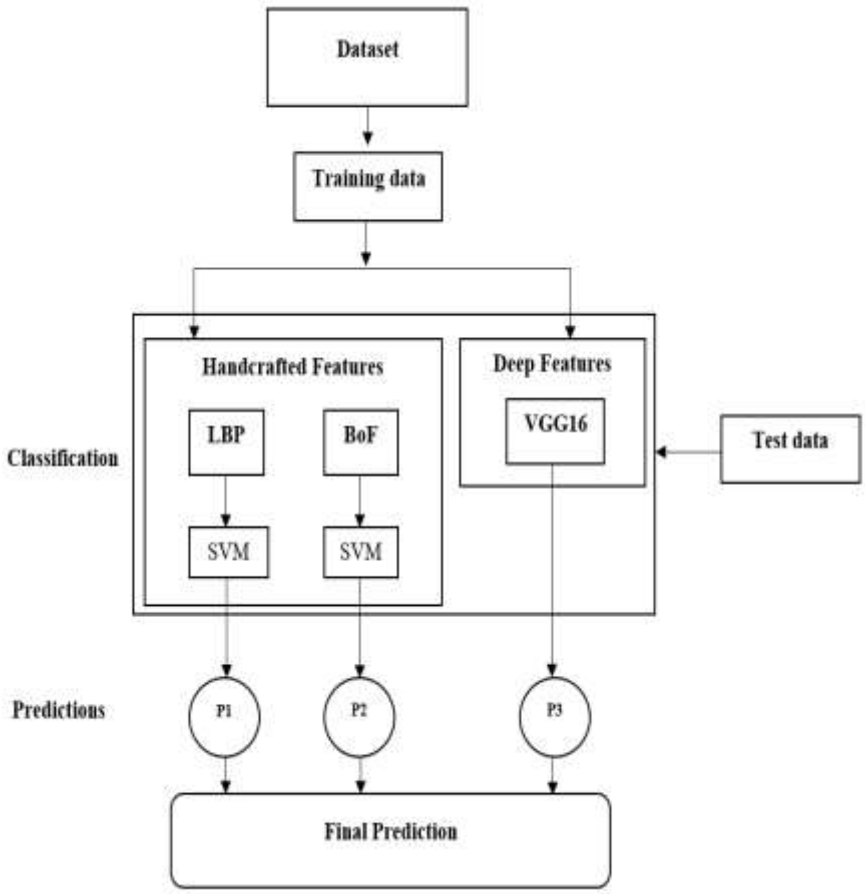

Fig. 2. Proposed System Architecture.

- In this work, MURA(Musculoskeletal Radiographs) [15], a large dataset of bone X-rays will be used.
- Each imagein the dataset belongs to one of the seven classes: elbow, finger, forearm, hand, humerus,shoulder, and wrist.(For example, see Fig. 3)

Hand **Shoulder**

Elbow

Fig. 3. Examples of Three X-ray Image Groups (Source: MURA Dataset)

- ➢ Initially following three models will be trained on all the images of the training set separately:
- LBP (see Section 3.1.1)
- BOF (see Section 3.1.2)
- VGG-16 (see Section 3.2.1)
- ➢ For every input, predictions from each model are calculated and then by using these predictions, the final prediction will be done.
- ➢ The final prediction will be done by combining the prediction from all the three models as a post-fusion method [5] with simple averaging computation.
- ➢ During validation when an input image is given, it undergoes the process and the output class label is generated.

IV. CONCLUSION

This paper provided a detailed review of combining the handcrafted visual features with a deep feature learned from a pre-trained Convolutional Neural Network for the classification of X-ray images. The pre-trained DCNNs were able to transfer the knowledge of image representation learned from natural image datasets to specific image classification tasks.This combination approach reduces the limitations of handcrafted and deep features when used individuallyand indeed improves the classification performance.Thereby resulting in a good precision rate, which is the most important factor for medical image classification.

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