Wood Texture Classification using GLCM and LBP

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***Abstract* - Texture classification is a challenging area in AI based research focusing on identifying the tactile surfaces of objects and scenes through the visual inspection of images. In this work, we propose to classify macroscopic images of wood species using texture descriptors and machine learning techniques. Several researches have been conducted using microscopic images of wood sections. The difficulty in practical usage of models trained in microscopic images led us to experimenting on macroscopic image datasets. We observed a significant need in developing wood recognition models to identify wood species of normal images captured using simple camera lens.**

***Index Terms* – Texture classification, GLCM, LBP, PCA.**

I.INTRODUCTION

The visual or tactile surface qualities and appearance of any- thing can be roughly characterized as texture. Various natural and manufactured data have texture like trees, wood, and cloth. Despite its relevance and prevalence in picture data, there is no systematic technique or concept for texture analysis. Texture can be defined as the surface property of generalized objects. While the weave of fabric kind is determined by visualizing the weaving patterns, the wood grains can determine the wood species. Briefly, the structural arrangement of surfaces is revealed through its texture.

In terms of a given image, texture defines the repeated patterns of pixel intensities that vary locally. Generally, two main steps are followed to determine the category of a texture image. First, several texture features are extracted from a given image. These features find correlations between pixel values over a certain range in the image. The features defining texture are also called texture descriptors. Secondly, the extracted descriptors are used to assign class memberships to each image through a train and test procedure. Fig [1] represents the general flow of a texture classification procedure.

Fig. 1. General flow of texture classification

The task of recognizing wood species is typically left to well-trained wood identification experts. A wood identification expert is evolved over years with experience until he is qualified to identify wood species with a great accuracy. Au- tomation of the wood identification process is in great demand in the industry as there is not enough wood identification experts available to meet the market need. An automated wood species recognition system may be learned once and replicated simply to satisfy the market need. For certain species of wood, a manual identification procedure can take up to many days or even weeks. But with the advent of efficient wood species recognition algorithms, the recognition time remains constant and close to real time to deliver accurate results. Moreover, the system can be used to maintain wood standards in the export industry. The model in the form of a smart phone application can be downloaded and used by any common man to identify and verify if he is actually buying what he is being told.

There are 3 different cuts to a wood namely the cross-sectional surface, the radial surface and the tangential surface. The cross-section surface of wood samples is preferred for wood identification because it retains and holds most charac- teristics of the wood evolved over time. Experts examine the wood surface with a 10x magnifying hand lens and match it to the detected features of different woof species.

Several researches have been conducted to automate wood species recognition. In [1] the energy statistics of the GLCM texture descriptor is used to classify the CAIRO dataset with an accuracy of 80%. [2] experiments with a Multi-layered neural network based on Back-propagation in which the GLCM features of the CAIRO dataset achieve a very high rate of recognition.

II. PROPOSED METHOD

Fig [2] schematically represents our proposed model. Combined texture features from the well-established GLCM and LBP are concatenated to achieve better results. We use macroscopic images of woods from the Greek territory for identification. Dimension of the extracted features are then reduced using the principal component analysis. These are then fed into the KNN classifier and trained. The trained wood recognition model is then tested and verified using reduced concatenated features of the test dataset.

A. Dataset

The WOOD-AUTH dataset [3] contains samples of normal wood structure from the Greek territory. 4272 cross sectional, radial and tangential wood section images of 12 different wood species including 3 softwood species and 9 hardwood species comprise the dataset. All images are captured from a distance

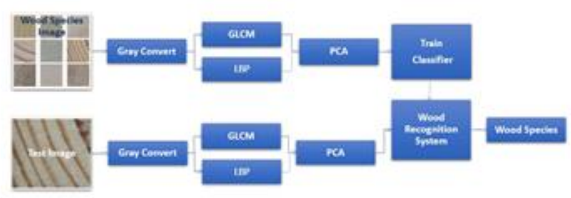

Fig. 2. Block diagram of the proposed wood species recognition model

of 15–20 cm and so are macroscopic in nature. They are also cropped to a standard size of 400 × 400 pixels. The major challenge and opportunity of the dataset is in identifying these macroscopic images that were not taken under ideal shooting conditions. The dataset is available with a train test split ratio of 7:3.

B. Feature Extaction

Every Image Classification and Object Recognition System requires the use of Feature Extraction (FE). The image pixels are mapped into the feature space is referred to as feature extraction [4]. In the proposed work the texture features are extracted by using two efficient feature extraction methods GLCM and LBP.These features are concatenated to form a new feature set. The most relevant features are extracted from the whole set of features by using a dimensionality reduction technique PCA (Principal Component Analysis).These are then fed into the KNN classifier for the purpose of texture classification.

1) GLCM: To estimate textural indices, the grey level co-occurrence matrix (GLCM) [5] takes into account the arrangements of pairs of voxels. Fig [3] represent the block diagram of GLCM Each image is analysed for six textural el- ements based on the grey level co-occurence matrix (GLCM). For each of the four directions, co-occurrence matrices are calculated: 0º, 45º, 90º and 135º degrees. Each co-occurrence matrices are computed in each of four angles [6], and the six texture descriptors are retrieved from them. The mathematical implementation of these textural elements as shown below.

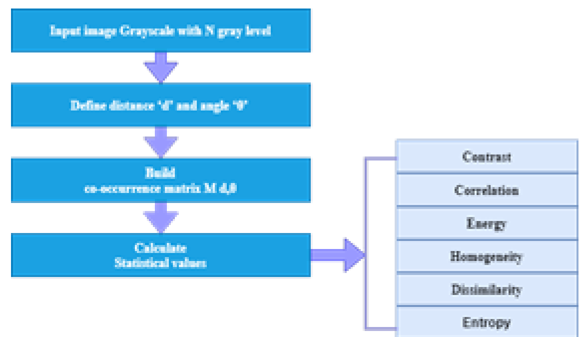

Fig. 3. Block diagram of GLCM

2) LBP: L0cal Binary Pattern (LBP) [7] is a texture de- scription operator that uses the signals of differences between neighbouring and central pixels to describe the texture. Fig [5]displays an example of how LBP values are calculated. the pixel in the middle A binary pattern can be made out of this binary code. If the pixel value is greater than or equal to the threshold, the neighbour pixel becomes 1. If the pixel value falls below a specified threshold, it is set to 0 threshold. Following that, the histogram will be constructed to calculate the frequency values of the binary pattern.

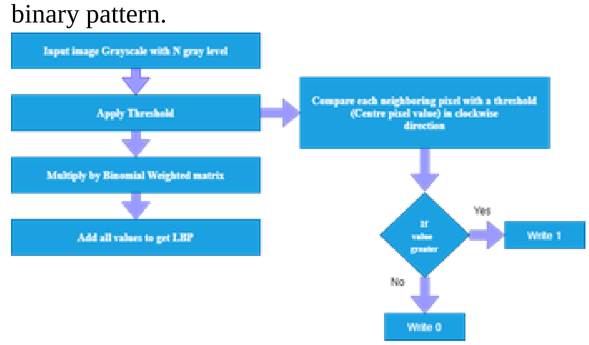

Fig. 4. Block diagram of LBP

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \quad (1)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (2)$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} (p_{ij})^2 \quad (3)$$

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (4)$$

$$\text{Dissimilarity} = \sum_{i,j=0}^{N-1} P(i,\, i) * |(i-j)| \quad (5)$$

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(p_{ij})\, p_{ij} \quad (6)$$

C. Dimensionality Reduction

Principal component analysis (PCA) [8] is the process of computing the principal components and using them to change the basis of the data, often simply using the first few and disregarding the rest. In the proposed work concatenated features from the efficient feature extraction methods GLCM and LBP are fed as into the PCA. The most relevant and valuable features are extracted from the whole set of features. Hence the model improve the performance due these most suitable features used for the texture classification.

D. Classification

Given the size and complexity of the texture classification problem, it makes sensible to start with a simple strategy to explore what results can be obtained. In this study, we employed the k-nearest neighbour technique as a classifier. An object is categorised by the majority vote of its neighbours, with the object being allocated to the most common class among its k closest neighbours. The KNN [9] algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other. Graphical representation of K- Nearest Neighbour as shown in fig 5.

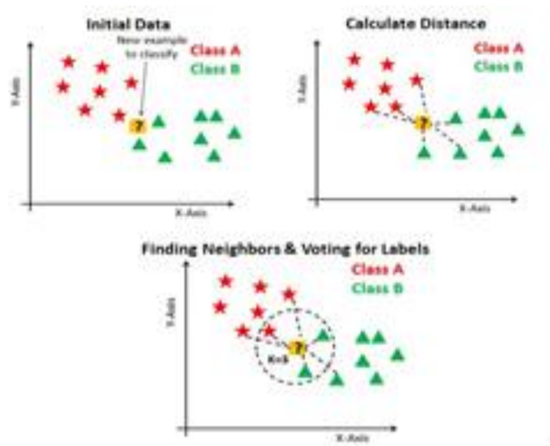

Fig. 5. Graphical representation of KNN

III. RESULT ANALYSIS

In the proposed work wood texture classification using GLCM and LBP are trained to generate a model. Here WOOD AUTH dataset is used to perform the classification task and finally it obtain an accuracy of 64 percentage.

IV. CONCLUSION

The proposed wood texture classification using GLCM and LBP improves the classification task . The deep learning tech- niques and combination of other machine learning classifiers with feature descriptors could be extend the classification accuracy of the model.

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