


# A Noval Approach for Object Recognition Using Decision Tree Clustering by Incorporating Multi-Level BPNN Classifiers and Hybrid Texture Features

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## ABSTRACT

This work proposes a novel approach to object recognition, particularly for human faces, based on the principle of human cognition. The suggested approach can handle a dataset or problem with a large number of classes for classification more effectively. The model for the facial recognition-based object detection system was constructed using a combination of decision tree clustering based multi-level Backpropagation neural network classifier-TFMLBPNN-DTC and hybrid texture feature (ILMFD+GLCM) and applied on NS and ORL databases. This model produced the classification accuracy ( $\pm$ standard deviation) of  $95.37 \pm 0.951877\%$  and  $90.83 \pm 1.374369\%$  for single input and  $96.58 \pm 0.5604582\%$  and  $91.50 \pm 2.850439\%$  for group-based decision for NS and ORL database respectively. The better classification results encourage its application to other object recognition and classification issues. This work's basic idea also makes it easier to improve classification management for a wide range of classes.

## KEYWORDS

BPNN, Context Window Based Texture of Pixels, Gray-Level Co-Occurrence Matrix, Human Cognition, Intensity Level Based Multifractal Dimension, Multi-level Backpropagation Neural Network

## 1. INTRODUCTION

A fundamental area of study in computer vision, deep learning, artificial intelligence, etc. is object detection. More difficult computer vision tasks, like target tracking, event detection, behavior analysis, and scene semantic understanding, require it as a necessary prerequisite. In order to create an effective object recognition system—in this case, face recognition—an attempt was made to integrate the human cognition principle. Numerous researchers have utilized decision tree-based classification approaches in a variety of fields, such as facial expression recognition (Salmam et al., 2016), group-based study to identify localized melanoma patients (Tsai et al., 2007), protein classification (Pepik et al., 2009), occlusions detection (Karthigayani & Sridhar, 2014), rule extraction for security analysis (Ren et

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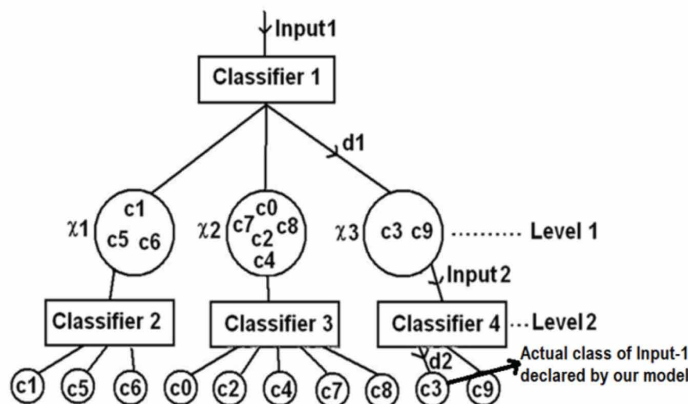
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al., 2006), gender classification (Khan et al., 2013), and hybrid classification based on decision tree and naïve bays methods (Muqasqas et al., 2014). In order to determine the most accurate class description for a given object, the decision tree concept takes into account the hierarchy of classes, just like humans do. This hierarchy starts at the top level of super-class hierarchy and moves down to the final hierarchy. However, there are very few classes at the base of the hierarchy, which makes it difficult for any classifier, including a human one, to handle due to its large number; as a result, the classes at this hierarchy must be grouped into a few clusters. For the classifier used to classify data into these super classes at this hierarchy, each of these clusters of classes can be thought of as a newly defined super class at the previous level of hierarchy. Similar methods have been applied to optical character recognition (Wilson et al., 1996) and face image recognition (Ebrahimpour et al., 2005) to increase classification accuracy. Using Fig. 1, the explanation that follows will help you understand this better. The majority of decision tree building techniques are based on decision clustering. Typically, decision trees are designed to handle a large number of classes. This method, of course, meets the needs of the majority of classifiers, most of which are unable to handle tasks involving a large number of classes. Figure 1 depicts a fictitious example of ten real classes, let's say  $c_1, c_2, c_3, \dots, c_{10}$ . In this case, at level 1 the original classes are merged to form super class's  $\chi_1, \chi_2$  and  $\chi_3$  for which classifier 1 is employed to get decision,  $d_1$  for class  $\chi_3$  at level 1. Next, for this decision as input, classifier 4 is invoked to reach the final decision  $d_2$  for class  $c_3$ . The flow of decision is as follows:

In order to mathematically adopt the object recognition system based on temporal description of the object, another cognition analog was also developed as (10). They contend that “we are continuously associating views of objects to support recognition, and that we do so not only on the basis of the objects’ correlated appearance in time, but also on their physical similarity.” Another argument in favor of this is that research by Bruce et al. (1998) and Knight & Johnston (1997) has shown and demonstrated that face recognition based on video is preferable than using still images. Additionally, they discover that motion aids in the recognition of (familiar) faces more effectively when the images are negated, or appropriately thresholded. This concept inspired the creation of moving head posed videos, which were recorded from left to right and vice versa, in order to extract multiple facial images of the same person in various poses and create a database for the classification model created in this work. The Bayesian Probabilistic model, which replicates the repeated input feature and aids in identifying the object with a higher probability, also supports this idea.

Figure 1. The process of making decision using “decision clustering tree” (common approach): Here input-1 is classified by root level classifier-1 to superclass- $\chi_3$ , where classifier-4 is employed, which classifies its actual class: class-3

Input1  $\rightarrow$  Classifier 1  $\rightarrow d_1 \rightarrow c_3 \rightarrow$  Input2  $\rightarrow d_2 \rightarrow$  Classifier 4  $\rightarrow c_3$



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