KNN approach through various image equalization techniques on CIFAR10

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Abstract

The success of a machine learning system for picture recognition and classification relies on the accuracy and efficiency of feature extraction. Due to the evolution in the digital domain limitless multimedia is generated daily. This calls for the development of a reliable and visually appealing image revival system. In this research, we propose a shape and texture-based image retrieval system, which compares each query image to the photos in the repository using shape and textural facets and then finds images that fall under a predetermined similarity threshold. The proposed method makes use of a statistical strategy for retrieving images.Object identification is a crucial component of many real-world applications, making it one of computer vision's most important subfields. Yet, the detection of small objects has long been an important and challenging issue in the study of object detection.This paper explores the JPEGCF with KNN has the greatest accuracy result of 95.80%. The RGB with KNN produces the lowest accuracy result of 89.07%. The accuracy of the GF with KNN has 94.15%, FOHF with KNN is 93.90% and PHOG with KNN is 95.05%, respectively. Based on the findings the JPEG coefficient with KNN models performs well compare than other models.

Keywords: **KNN, JPEGCF, CIFAR10, FOHF, PHOG,Gabor Filter**

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I Introduction

In many engineering and computer vision applications, mutual classification of images is crucial. Image processing in medicine, classification-based robotics, and pattern recognition are just a few of the key sectors that make extensive use of classification techniques. When dealing with a vast image database, image categorization becomes an extremely difficult operation. Many people [1, 2, 3, 4, 5, and 6] have worked hard to develop a reliable classification method in order to address this difficult problem. For the most part, classification tasks are where the k-nearest neighbor (KNN) algorithm shines as a supervised machine learning approach. It's been put to good use in the field of object detection. The KNN is a supervised algorithm that uses the features and labels of the training data to make predictions about the classification of unlabeled data. By considering the k nearest training data points (neighbors), which are the closest to the query it is testing, the KNN algorithm is able to categorize datasets using a training model comparable to the testing query. When deciding on a final classification, the algorithm uses a majority voting rule. The KNN method is one of the simplest types of machine learning algorithms, and it is commonly employed in classification tasks due to its very flexible and intuitive design.

The rest of the paper is organized as follow: Section 2 outlines the related work. Section 3 introduces the proposed methodology, and the results and discussion are briefly discussed in Section 4. Finally, we conclude the paper in Section 5.

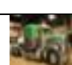
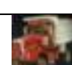
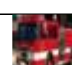
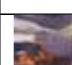
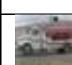
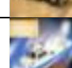
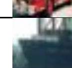
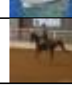
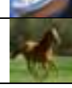
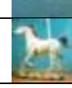
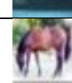
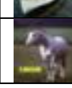
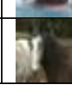
II Literature Survey

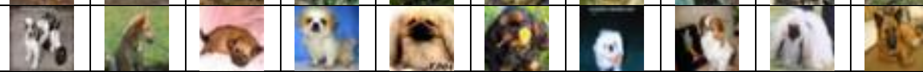
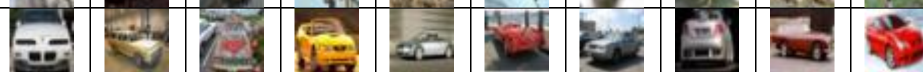
One of the most popular subfields in computer vision research is object recognition [1]. There are several methods to define an object identification system, but ultimately, all they do is search through images for features that correspond to stored 3D models of commonplace things [2, 3]. Based on this interpretation, the object identification system's behavior changes when background noise is present: If the image has very little noise, it likely contains a single object, and the system will attempt to determine if the detected image corresponds to a stored object representation. The system not only determines if a detected object is a match for a model in the database, but also determines distinctive attributes of objects, such as area in the image, in high clutter situations.Object identification [1, 2, 3, 4], picture classification [5, 6, 7, 8], and natural language processing [9, 10, 11] are just a few areas where machine learning has made significant strides in artificial intelligence. But, in the age of big data, we are confronting the challenge of exponential data expansion. More efficient means of computation are desperately needed. The quantum system endowed with inherent parallelism appears to be an excellent option. Several quantum algorithms exhibiting quantum superiority have been proposed as a result of the in-depth research into quantum technology [12, 13,14,15]. Scientists discovered that by combining quantum and machine learning techniques, algorithm performance might be enhanced. This gave rise to the idea of quantum machine learning [16,17]. It has been shown that many quantum machine learning algorithms [18, 19,20,21,22] outperform their classical analogues. Researchers' attention has been drawn to a KNN algorithm with a straightforward concept but significant temporal complexity in this setting. When classifying, it takes almost no background knowledge [23]. K-nearest neighbors (KNN) search and similarity computation are two major components of KNN. Several quantum approaches to these two procedures have been presented in recent years. To determine the cosine distance between two vectors, the swap test quantum circuit was invented by Harry Buhrman et al. in 2001 [24]. In 2013, Lloyd et al. [25] developed a swap test circuit–based quantum Euclidean distance estimator. For numerical data, a quantum K-nearest neighbour technique based on Hamming distance is proposed [28,29]. In 2014, Wiebe et al. developed a quantum nearest neighbour algorithm [26] that utilizedDürr and Hyer's algorithm for determining the minimal value in a database [27].

III Materials and Methods

This work considers randomly selected 100 images form the CIFAR-10 dataset which has 60000colour images with of 32x32 dimension. These 100 images has categorized in 10 classes, each class has10 tiny images. The classes are categorized like truck, ship, horse, frog, dog, deer, cat, bird, auto mobile and airplane images.

Table1: CIFAR 10 dataset

S.No	Name of the Images	1	2	3	4	5	6	7	8	9	10
1	truck										
2	ship										
3	horse										

4	frog	
5	dog	
6	deer	
7	cat	
8	bird	
9	automobile	
10	airplane	

The following methods has been applied in Weka 3.9.5 open source mining tool for getting an optimal outcome.

Methods:

The following method are applied in this research work

- Borrowed dataset
- Data preprocessing
- Apply for various histogram techniques
- Gabor Filter
- Jpeg Coefficients Filter
- PHOG Filter
- RGB Color Histogram
- Fuzzy Opponent Histogram Filter
- Implement KNN
- Evaluate models
- Find a best Model

To produce an efficient result, these strategies were applied in Weka. 3.9.5. This study uses the total dataset and uses tenfold cross validation for all categories.

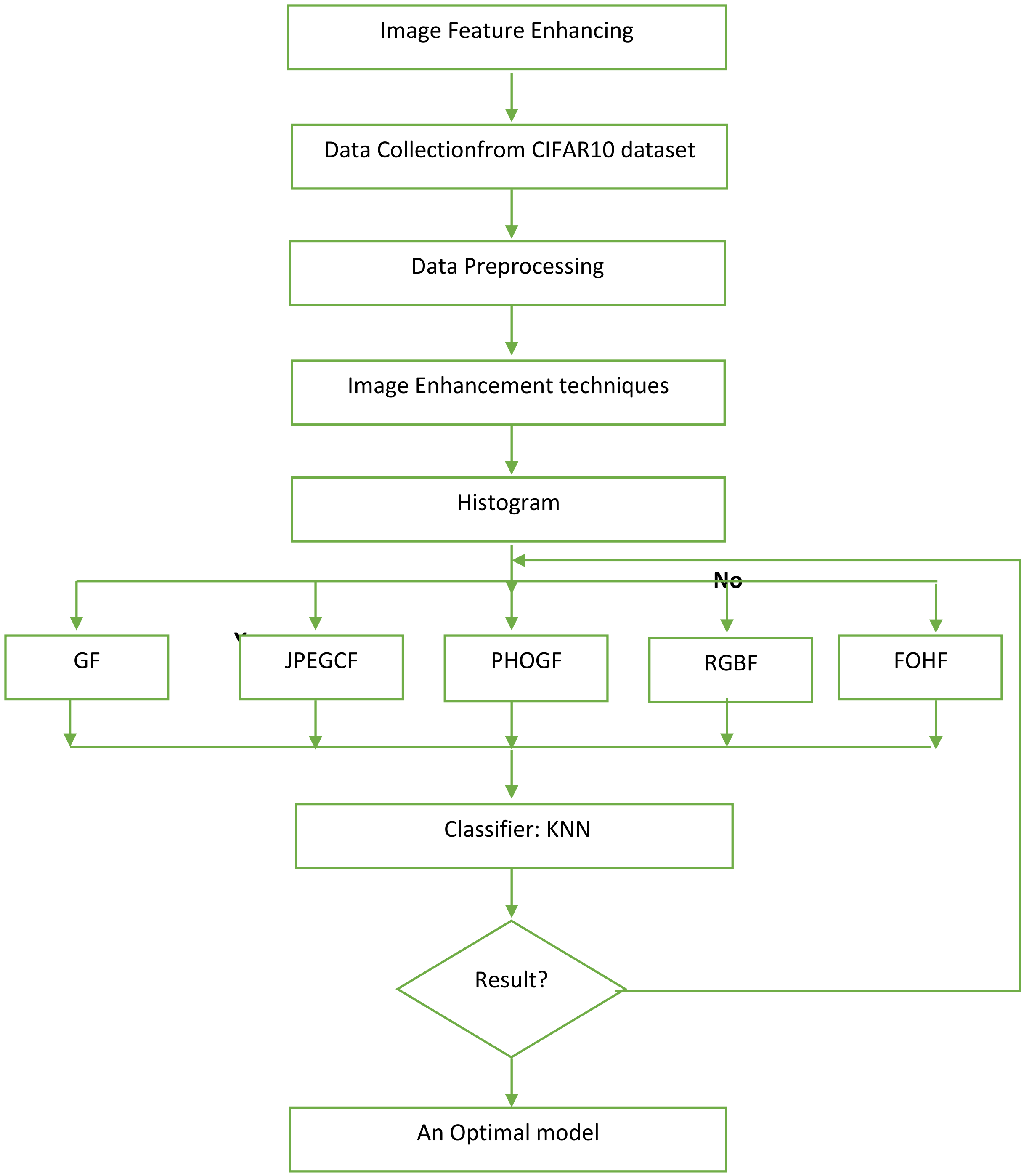


Figure 1: Proposed System

Table 2: Performance of selected classifiers

S.No	Classifiers	Accuracy	Precision	Recall	F-Measure	MCC	Kappa
1	GF with KNN	94.15%	0.95	0.95	0.95	0.67	0.66
2	JPEGCF with KNN	95.80%	0.97	0.97	0.97	0.76	0.77
3	PHOG with KNN	95.05%	0.96	0.97	0.95	0.69	0.76
4	RGB with KNN	89.07%	0.92	0.91	0.90	0.65	0.65
5	FOHF with KNN	93.90%	0.94	0.94	0.95	0.67	0.69

The above table shows that the various selected ensemble classifiers.

The GF with KNNresults in an accuracy level of 94.15%, a precision value of 0.95, a recall value of 0.95, an F-Measure value of 0.95, an MCC value of 0.67 and a kappa statistic value of 0.66.The JPEGCF with KNN results in an accuracy level of 95.80%, a precision value of 0.97, a recall value of 0.97, an F-Measure value of 0.97,an MCC value of 0.76 and a kappa statistic value of 0.77. The PHOG with KNN produces a yield of 95.05% an accuracy, a precision value of 0.96, a recall of 0.97, an F-Measure of 0.95, an MCC of 0.69 and a kappa statistic of 0.76. The RGB with KNNproduces accuracy level 89.07%, a precision value 0.92, recall value 0.91, an F-Measure value 0.90,anMCC value 0.65 and a kappa statistic value 0.65.The FOHF with KNNhas an accuracy level of 93.90%, a precision value of 0.94, a recall value of 0.94, an F-Measure value of 0.95, an MCC value of 0.67 and a kappa statistic value of 0.69.

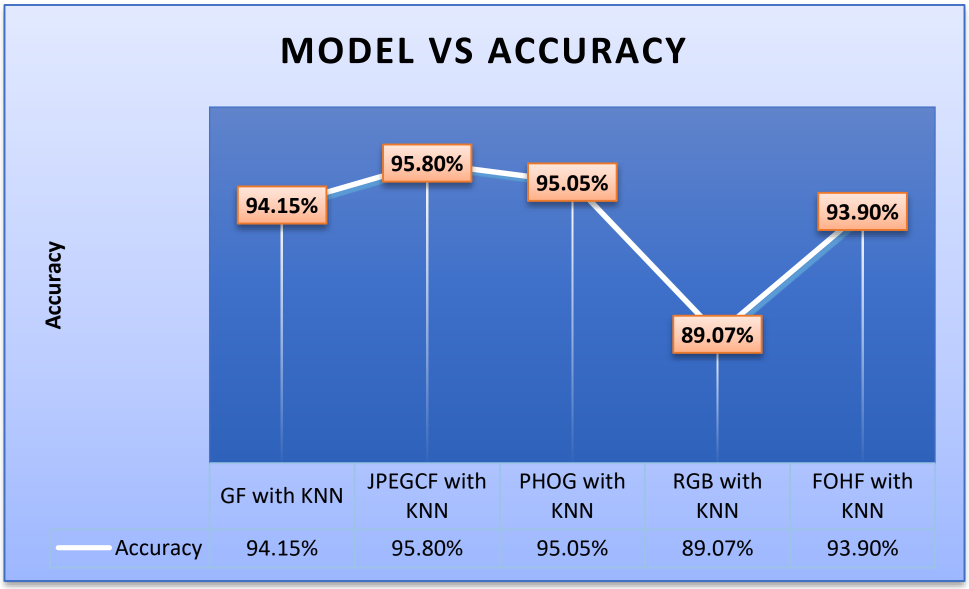


Figure 2: Performance of Ensemble classifiers with their accuracies

The above diagram shows that the accuracy performances of selected models. The JPEGCF with KNNhas the greatest accuracy result of 95.80%. The RGB with KNN produces the lowest accuracy result of 89.07%. The accuracy of the GF with KNN has 94.15%, FOHF with KNN is 93.90% and PHOG with KNN is 95.05%, respectively.

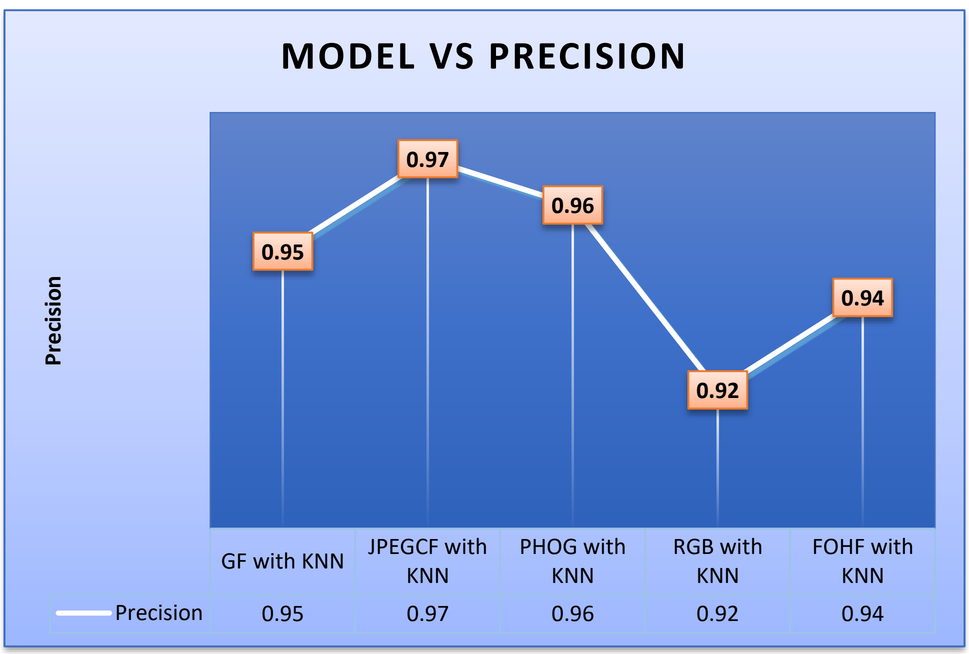


Figure 3: Performance of Ensemble Classifiers with their Precision values

The precision performances of selected models are depicted in the diagram above. The JPEGCF with KNN has 0.97 of precision value which is highest value. RGB with KNN has lowest value 0.92. The FOHF,GF and PHOG with KNN are having precision values 0.94,0.95,and 0.96 , respectively.

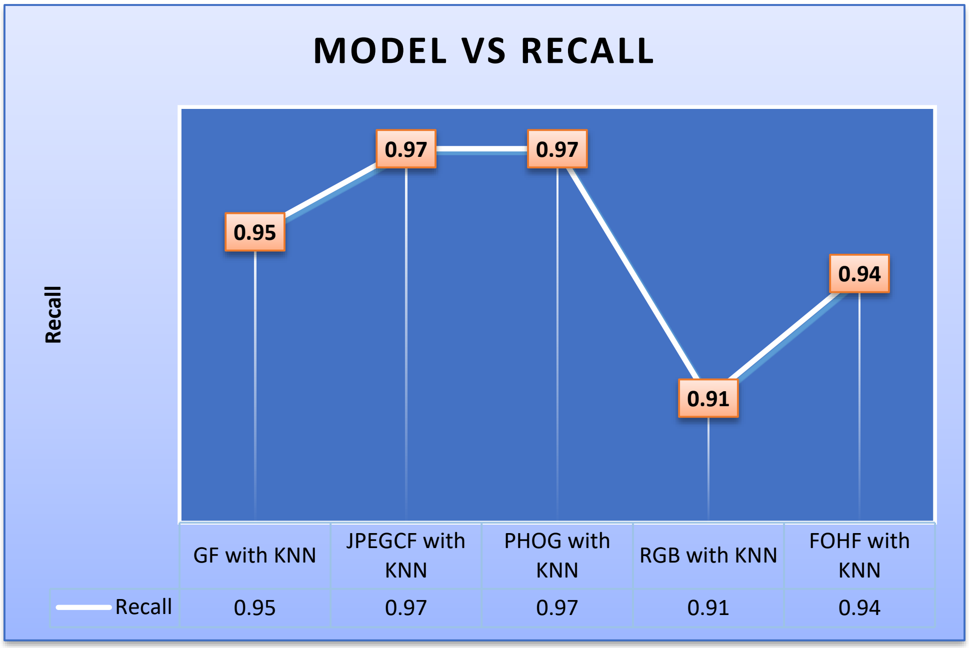


Figure 4: Performance of Ensemble Classifiers with their Recall values

The graph above depicts the recall performances of selected models. The JPEGCF and PHOG filters with KNN have same recall value which is 0.97. The least recall value is 0.91 which is RGB filter with KNN model. The FOHF and GF with KNN have 0.94 and 0.95 of recall values, respectively.

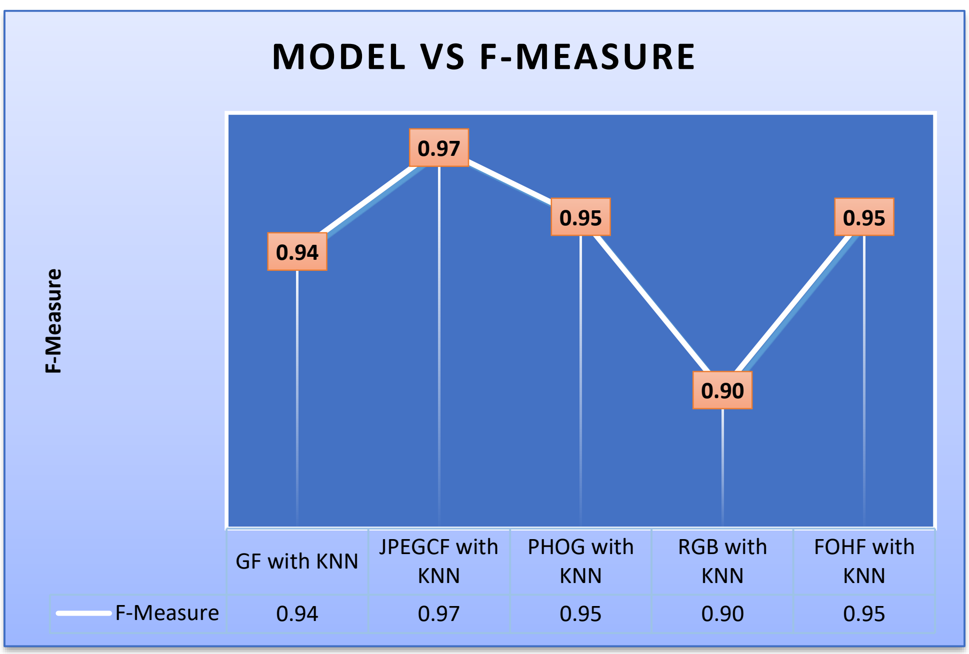


Figure 5: Performance of Ensemble Classifiers with their F-Measure values

The graph above depicts the F-Measure performances of selected models. The JPEG with KNN model is having greatest value 0.97 of F-measure. The RGB with KNN model has lowest value 0.90. The PHOG and FOHF with KNN value has same which is 0.95 and GF with model has 0.94 of F-measure value.

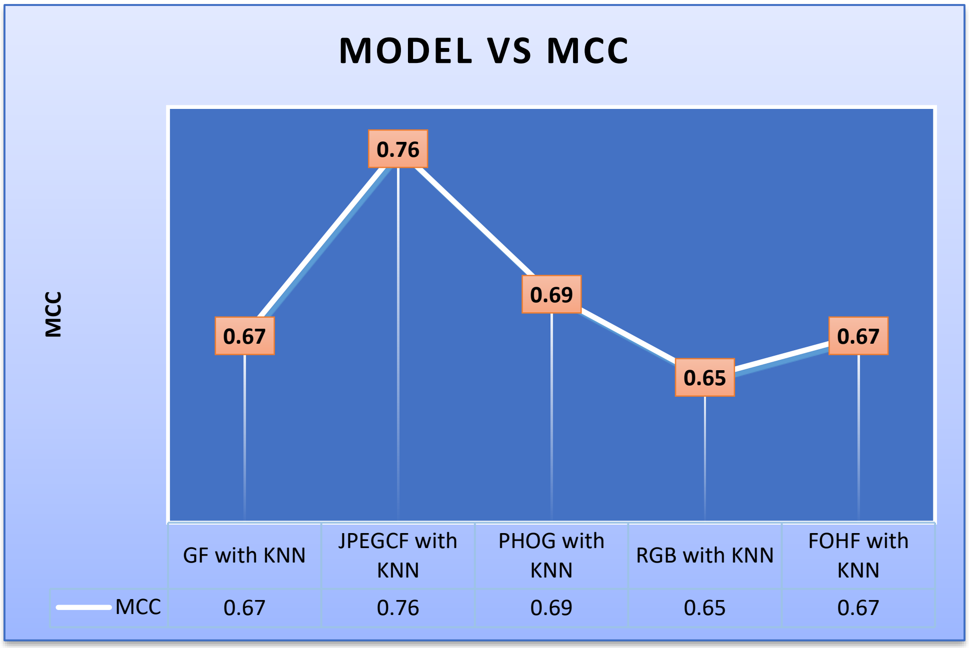


Figure 6: Performance of Ensemble Classifiers with their MCC values

The graphic above depicts the MCC performance of selected models. The JPEGCF with KNN model has highest MCC value which is 0.76 and least value is 0.65 (RGB with KNN model). The FOHF and GF with KNN models are having same MCC value 0.67. The PHOGF has 0.69 of MCC value.

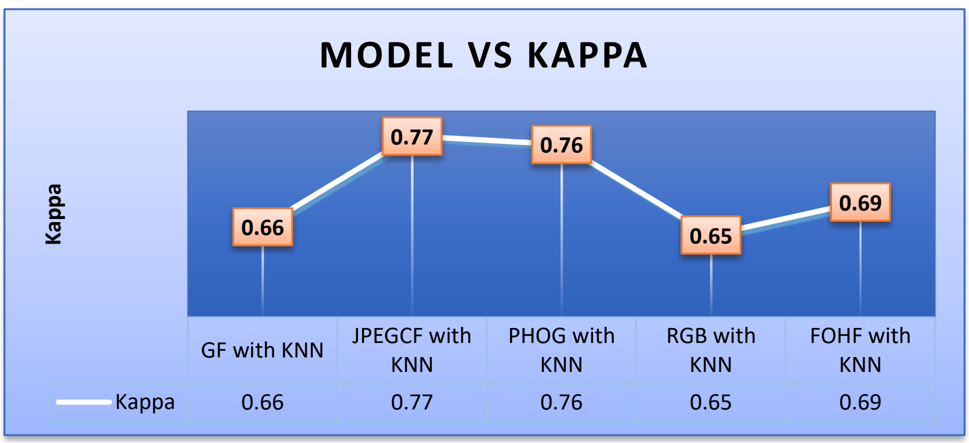


Figure 7: Performance of Ensemble classifiers with their Kappa statistic values

The graph above depicts the kappa value performances of selected models.The JPEGCF with KNN has highest value 0.77 of kappa. The RGB with KNN model has lowest value which is 0.65 of kappa. The GF, FOHF and PHOG with KNN models are 0.66, 0.69 and 0.76 of kappa values respectively.

V Conclusions

Based on this study's findings, GF with KNN results in an accuracy level of 94.15%, a precision value of 0.95, a recall value of 0.95, an F-Measure value of 0.95, an MCC value of 0.67 and a kappa statistic value of 0.66. The JPEGCF with KNN results in an accuracy level of 95.80%, a precision value of 0.97, a recall value of 0.97, an F-Measure value of 0.97,an MCC value of 0.76 and a kappa statistic value of 0.77. The PHOG with KNN produces a yield of 95.05% an accuracy, a precision value of 0.96, a recall of 0.97, an F-Measure of 0.95, an MCC of 0.69 and a kappa statistic of 0.76. The RGB with KNN produces accuracy level 89.07%, a precision value 0.92, recall value 0.91, an F-Measure value 0.90,anMCC value 0.65 and a kappa statistic value 0.65.The FOHF with KNN has an accuracy level of 93.90%, a precision value of 0.94, a recall value of 0.94, an F-Measure value of 0.95, an MCC value of 0.67 and a kappa statistic value of 0.69.The JPEGCF with KNN has the greatest accuracy result of 95.80%.The JPEGCF with KNN has 0.97 of precision value which is highest value. RGB with KNN has lowest value 0.92.. The JPEGCF and PHOG filters with KNN have same recall value which is 0.97.The JPEG with KNN model is having greatest value 0.97 of F-measure.The JPEGCF with KNN model has highest MCC value which is 0.76 and least value is 0.65 (RGB with KNN model).The JPEGCF with KNN has highest value 0.77 of kappa. The RGB with KNN model has lowest value which is 0.65 of kappa. This work recommends that the JPEGCF with KNN models based on their outcome compare with other models.

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