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Classification of Image through various image histogram techniques on CIFAR10 Datasets

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Abstract

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 theBinary Pyramid PatternFilter with Support Vector Machine perform well as well it showing an efficient outcome. It has the greatest accuracy result of 85.80%.The Binary Pyramid PatternFilter with Support Vector Machine produces the greatest precision result of 0.87.The Binary Pyramid PatternFilter with Support Vector Machine produce the maximum recall of 0.87.The Binary Pyramid PatternFilter with Support Vector Machine has the greatest F-Measure result of 0.87.The Binary Pyramid PatternFilter with Support Vector Machine model has the highest MCC value of 0.66.The Binary Pyramid PatternFilter with Support Vector Machine model has the greatest kappa value of 0.67. The Binary Pyramid PatternFilter with Support Vector Machine model has an optimal results compare with other models.

Keywords: Binary Pyramid Pattern Filter, SVM, ACCF, CLF

I Introduction

The supervised machine learning approach known as a Support Vector Machine (SVM) can be used for both classification and regression. In this piece, we will explore the use of SVMs to the classification of images.A computer sees a picture as a flat grid of pixels when it analyses it. If the image has a resolution of 200 pixels across and 200 pixels in height, the corresponding dimensions of the array will be 200 by 200 by 3. The width and height of the image correspond to the first two dimensions, while the RGB colour channels correspond to the third. Each value in the array represents the pixel's brightness and can take on a value between 0 and 255.The first step in utilising a support vector machine (SVM) to classify a picture is to extract features from it. Pixel colour values, edge recognition, and texture analysis are all examples of features. As soon as the features have been extracted, they can be fed into the SVM algorithm.The SVM algorithm is effective because it locates the hyperplane that divides the feature space into distinct classes. To maximise the margin, or the distance between the classes' nearest points, SVMs seek out the hyperplane that best separates them. The namesake vectors for the points nearest to the hyperplane.

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

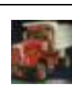
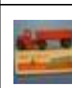
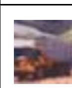
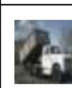
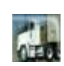
The advent of deep learning [1-8] has led to amazing advancements in object detection in recent years. Small-object detection remains a challenge in the realm of object recognition [9]. According to the Common Object Classification (COCO) dataset, a standard in the field of object detection, small objects are those having pixel areas of less than 32 32. Detecting tiny objects is challenging for three key reasons.

To begin, there is a direct correlation between the size of an object and the number of semantic features it possesses. Second, there are less instances of tiny targets, which may lead the object detection model to focus more on finding large targets. Finally, it's tough to find equivalents to the anchors. Because the ground truth for a small object is so low, the IoU between the ground truth and the anchor is too low if the anchor-based approach is used and the anchor is incorrectly configured. It's possible that this will train the network to view the anchors as bad examples.

Multiscale detection [10, 11], multiscale feature fusion [12, 13], data augmentation [9, 14], and resolution improvement [15, 17] are some of the most common methods used by modern object detection algorithms to increase the performance of small object recognition. Feature pyramid networks were proposed by Lin et al. [13]. (FPNs). By upsampling, it combines high-dimensional and low-dimensional feature maps. As a result, the detection performance of small targets is enhanced, and the resolution of the feature map is increased. In order to communicate the positional features from the bottom up, PANet [16] included a path following the FPN. The multiscale feature fusion suggested by EfficientDet [18-20] is a simple and quick bidirectional feature pyramid network (BiFPN). The output feature maps are typically influenced in diverse ways by the input resolutions.[21-25] Consequently, BiFPN implements learnable weights to simultaneously apply top-down and bottom-up multiscale feature fusion, therefore learning the significance of various input features. Using supplementary data, the enhanced the detection effect of tiny objects.[26-28] To address the issue of having insufficient training data including little objects, we can oversample these photos or employ the copy-and-paste technique. By using multiscale detection, SSD increased the capability of detecting small targets. For smaller targets, lower-dimensional feature maps are used, whereas higher-dimensional feature maps are employed for bigger targets.[29-30] The trained detector in SOD-MTGA [30-32] first obtains the subgraph containing small targets, which is then used by the generator to produce the corresponding high-definition image, and the discriminator is in charge of validating the authenticity of the generated image and making predictions about the category and location of small targets.

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.

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

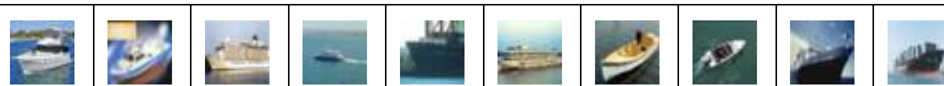
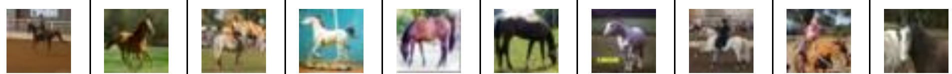
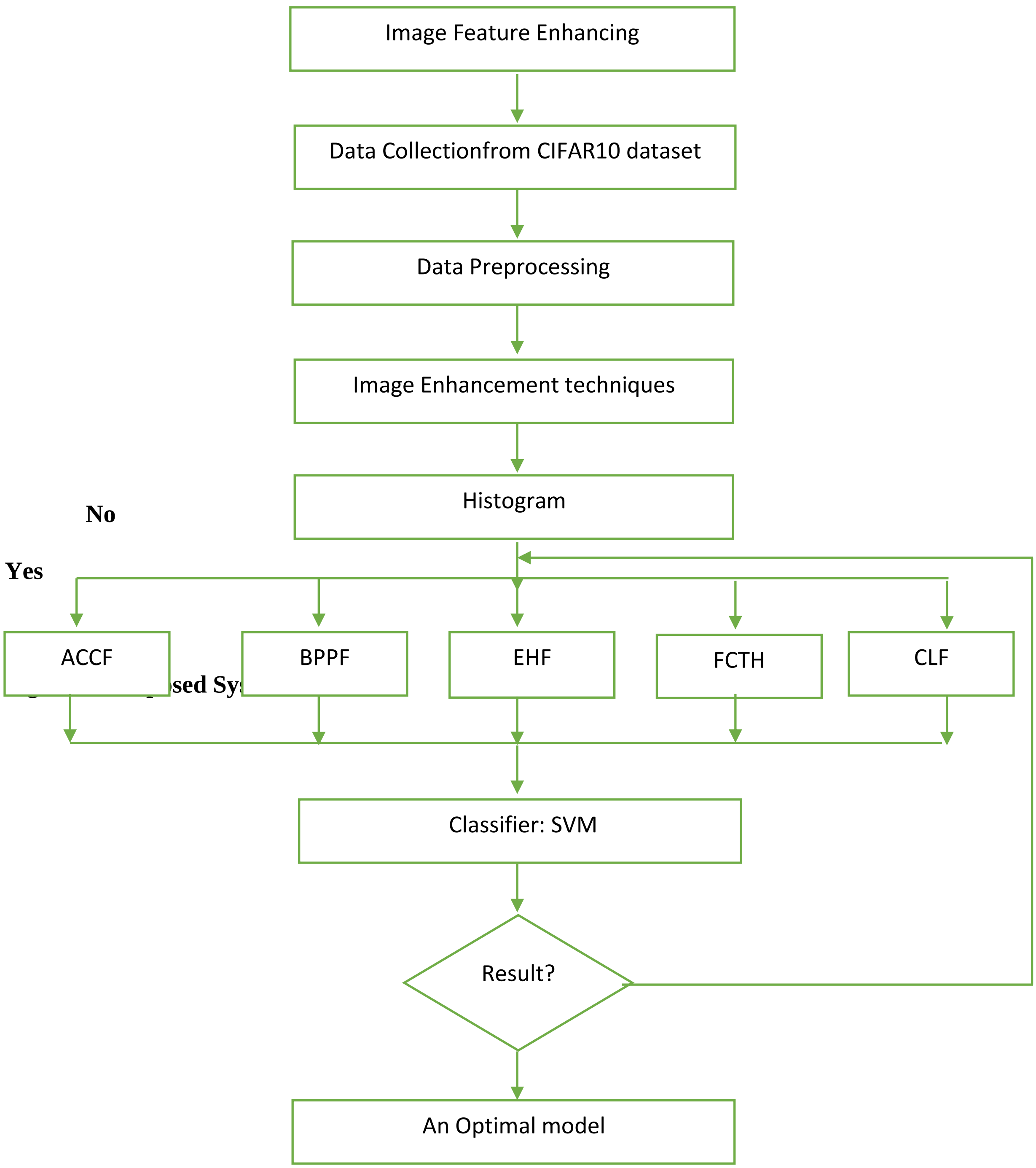
2	ship	
3	horse	
4	frog	
5	dog	
6	deer	
7	cat	
8	bird	
9	automobile	
10	airplane	

Table1: CIFAR 10 dataset

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:
- Auto Color Correlogram Filter
- Binary Patterns Pyramid Filter
- Color Layout Filter
- Edge Histogram Filter
- Fuzzy Color And Texture Histogram
- Implement Support Vector Machine
- Evaluate models
- Find abest Model

Table 2: Performance of selected classifiers

S.No	Classifiers	Accuracy	Precision	Recall	F-Measure	MCC	Kappa
1	ACCF with SVM	85.15%	0.86	0.86	0.85	0.58	0.57
2	CLF with SVM	86.05%	0.87	0.88	0.86	0.60	0.61
3	EHF with SVM	80.07%	0.83	0.82	0.81	0.56	0.56
4	FCTH with SVM	84.90%	0.85	0.85	0.86	0.58	0.60
5	BPPF with SVM	86.80%	0.88	0.88	0.88	0.67	0.68

The above table shows that the various selected ensemble classifiers.

The ACCF with SVMresults in an accuracy level of 85.15%, a precision value of 0.86, a recall value of 0.86, an F-Measure value of 0.85, an MCC value of 0.58 and a kappa statistic value of 0.56.

The CLF with SVMresults in an accuracy level of 86.05%, a precision value of 0.87, a recall value of 0.88, an F-Measure value of 0.86,an MCC value of 0.60 and a kappa statistic value of 0.61.

The EHF with SVMproduces a yield of 80.07% an accuracy, a precision value of 0.83, a recall of 0.82, an F-Measure of 0.81, an MCC of 0.56 and a kappa statistic of 0.56.

The FCTH with SVMproduces accuracy level 84.90%, a precision value 0.85, recall value 0.85, an F-Measure value 0.86,anMCC value 0.58 and a kappa statistic value 0.60.

The BPPF with SVM has an accuracy level of 86.80%, a precision value of 0.88, a recall value of 0.88, an F-Measure value of 0.88, an MCC value of 0.67 and a kappa statistic value of 0.68.

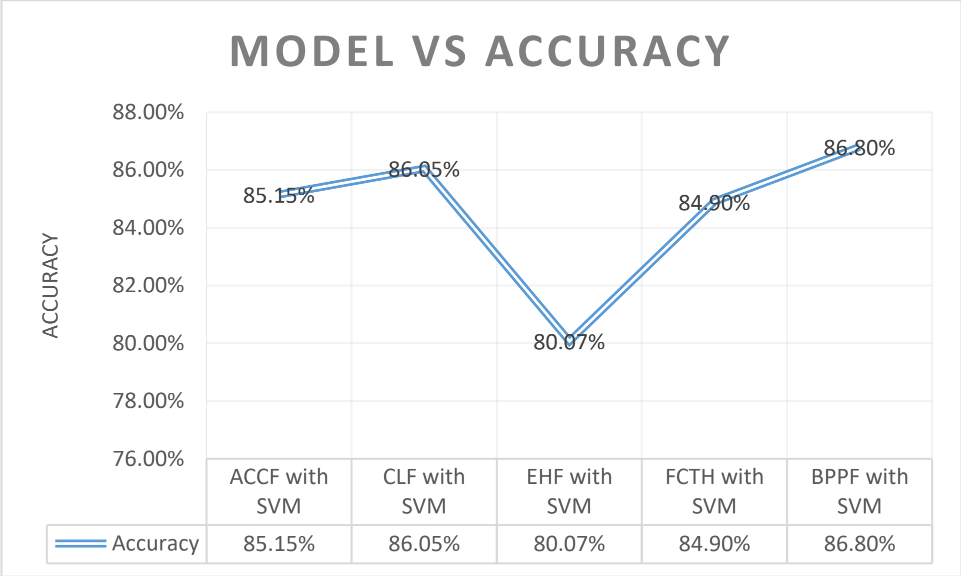


Figure 2: Performance of Ensemble classifiers with their accuracies

The above diagram shows that the accuracy performances of selected models. The BPPF with SVM has the greatest accuracy result of 86.80%. The EHF with SVMproduces the lowest accuracy result of 80.07%. The accuracy of the FCTH with SVM, ACCF with SVM, and CLF with SVMis 84.90%, 85.15%, and 86.05%, respectively.

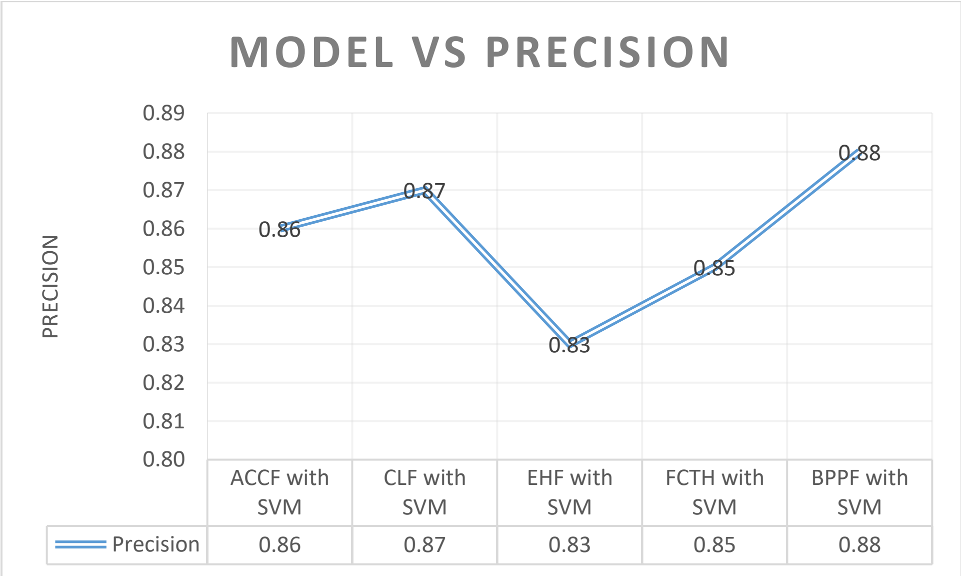


Figure 3: Performance of Ensemble Classifiers with their Precision values

The precision performances of selected models are depicted in the diagram above. The BPPF with SVM produces the greatest precision result of 0.88. The EHF with SVMproduces the lowest accuracy result of 0.83. The precision levels of the FCTH with SVM, ACCF with SVM, and CLF with SVMare 0.85, 0.86, and 0.87, respectively.

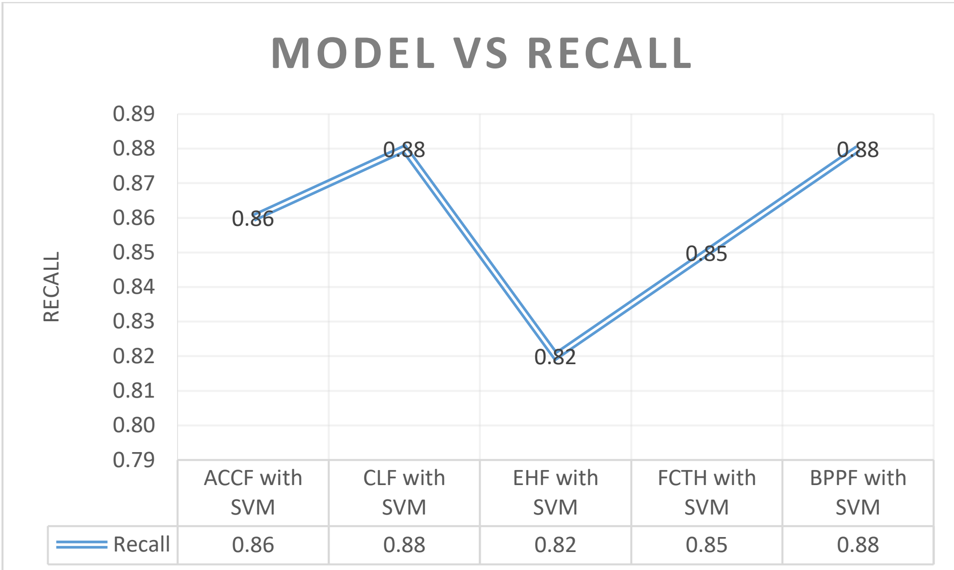


Figure 4: Performance of Ensemble Classifiers with their Recall values

The graph above depicts the recall performances of selected models. The BPPF with SVM and CLF with SVMproduce the maximum recall of 0.88. The EHF with SVMproduces the lowest recall result of 0.82. The recall levels for the EHF with SVMand ACCF with SVM are 0.85 and 0.86, respectively.

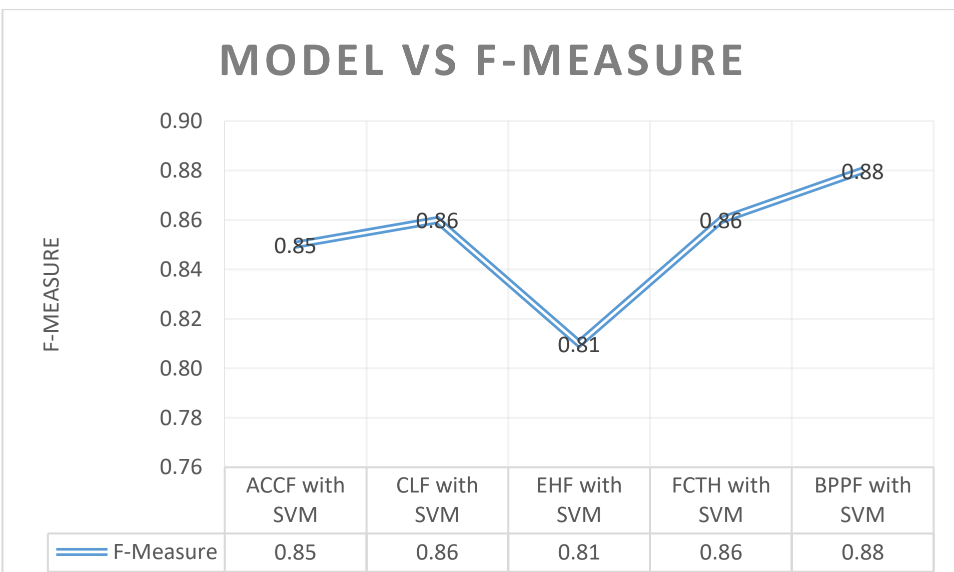


Figure 5: Performance of Ensemble Classifiers with their F-Measure values

The graph above depicts the F-Measure performances of selected models. The BPPF with SVM has the greatest F-Measure result of 0.88. The EHF with SVMproduces the lowest F-Measure result of 0.81. The ACCF with SVMhas an F-Measure of 0.85, whereas the FCTH with SVMand CLF with SVMhave the same value of 0.86.

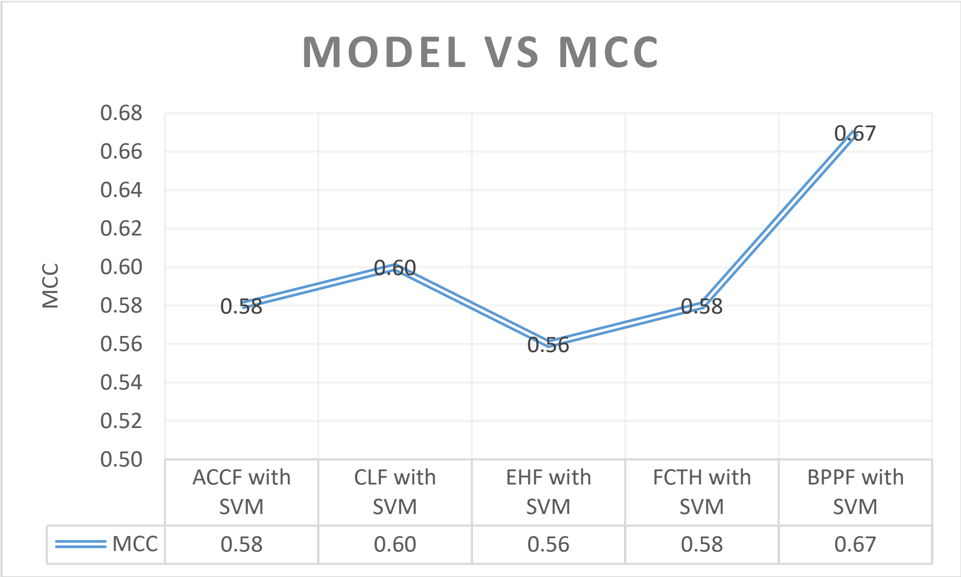


Figure 6: Performance of Ensemble Classifiers with their MCC values

The graphic above depicts the MCC performance of selected models. The BPPF with SVM model has the highest MCC value of 0.66. The EHF with SVMproduces the lowest MCC result is 0.56. The remainder of the models, such as the ACCF with SVMmodel and FCTH with SVM have the same MCC value of 0.58. The MCC value for CLF with SVM 0.60.

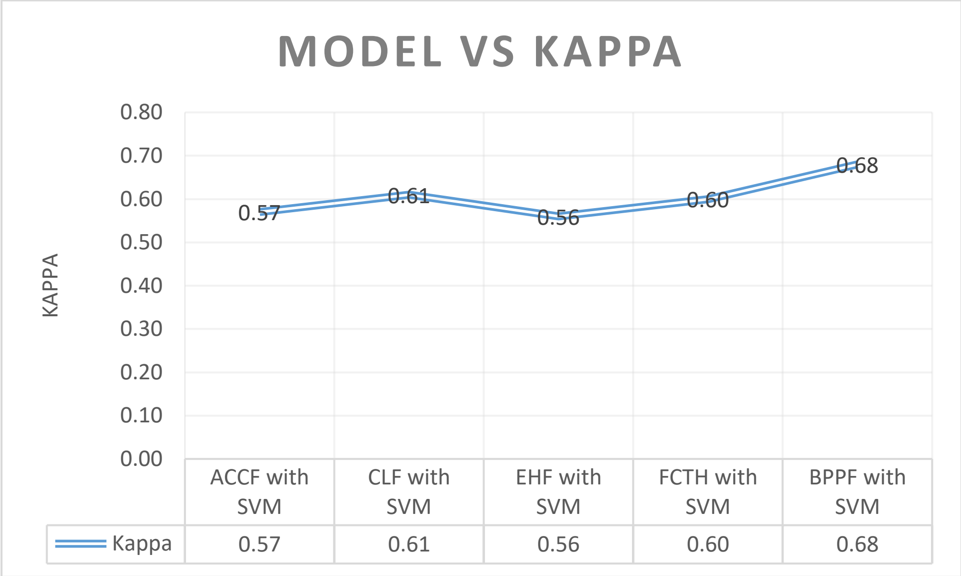


Figure 7: Performance of Ensemble classifiers with their Kappa statistic values

The graph above depicts the kappa value performances of selected models. The BPPF with SVM model has the greatest kappa value of 0.68. The EHF with SVMproduces the lowest kappa result of 0.56. Other models with kappa values between 0.57 and 0.61 are ACCF with SVM, FCTH with SVM, and CLF with SVM.

V Conclusions

Based on this study's findings, the ACCF with SVM results in an accuracy level of 85.15%, a precision value of 0.86, a recall value of 0.86, an F-Measure value of 0.85, an MCC value of 0.58 and a kappa statistic value of 0.56.The CLF with SVM results in an accuracy level of 86.05%, a precision value of 0.87, a recall value of 0.88, an F-Measure value of 0.86,MCC value of 0.60 and a kappa statistic value of 0.61. The EHF with SVM produces a yield of 80.07% an accuracy, a precision value of 0.83, a recall of 0.82, an F-Measure of 0.81, an MCC of 0.56 and a kappa statistic of 0.56. The FCTH with SVM produces accuracy level 84.90%, a precision value 0.85, recall value 0.85, an F-Measure value 0.86,an MCC value 0.58 and a kappa statistic value 0.60.The BPPF with SVM has an accuracy level of 86.80%, a precision value of 0.88, a recall value of 0.88, an F-Measure value of 0.88, an MCC value of 0.67 and a kappa statistic value of 0.68. The BPPF with SVM has the greatest accuracy result of 86.80%, aprecision result of 0.88, a recall of 0.88, an F-Measure result of 0.88, anMCC value of 0.67and akappa value of 0.68.This model recommends the BPPF with SVM compare with other models.

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