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The Novel ML Approaches on Wheat Disease by CLF and FOHF of Image Equalization Techniques

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Abstract:

Crop diseases and insect pests are the most significant obstacles to agricultural production. Consequences include a decrease in crop yields and the obstruction of the long-term development of high-quality, high-efficiency agriculture. Rapid and accurate detection of wheat leaf disease categories promotes early deployment of field control and improvement of wheat yield and quality. It's no exaggeration to say that wheat is one of the world's most vital crops. Wheat leaf diseases, though, severely hamper development. The quality of wheat and the agricultural economy rely on prompt and correct identification of wheat leaf diseases. This work propose an integrated machine learning technique, According to the results of this study, when compared to other models, the Fuzzy Opponent Histogram Filter that makes use of Bayes Net performs the best. The Fuzzy Opponent Histogram Filter with Bayes Net gives best outcome which is 97% of accuracy. The Color Layout Filter with Sequential Minimal Optimizer and Color Layout Filter with Ada Boost has same as well least outcome which is 83% of accuracy. The Fuzzy Opponent Histogram Filter with Bayes Net has 0.97 of precision which is best result than other models. The Color Layout Filter with Sequential Minimal Optimizer and Color Layout Filter with Ada Boost has 0.84 of precision which are least as well same outcome. The Fuzzy Opponent Histogram Filter with BN has 0.97 of recall which is best result than other models. The Color Layout Filter with Sequential Minimal Optimizer and Color Layout Filter with Ada Boost has 0.83 of recall which are least as well same outcome. The Color Layout Filter with Sequential Minimal Optimizer and Color Layout Filter with Ada Boost has same as well as least outcome which is 0.75 of MCC. The Fuzzy Opponent Histogram Filter with Bayes N has best result which is 0.95 of MCC. The Color Layout Filter with Sequential Minimal Optimizer and Color Layout Filter with Ada Boost has same as well as least outcome which is 0.83 of F-Measure. The Fuzzy Opponent Histogram Filter with Bayes Net has best result which is 0.97 of F-Measure. The Color Layout Filter with Sequential Minimal Optimizer and Color Layout Filter with Ada Boost has same as well as least outcome which is 0.75 of Kappa. The Fuzzy Opponent Histogram Filter with Bayes Net has best result which is 0.95 of Kappa value. The Fuzzy Opponent Histogram Filter with Bayes Net has highest ROC 0.99 and Color Layout Filter with Sequential Minimal Optimizer has 0.90 of ROC which is least value compare than other models. The Fuzzy Opponent Histogram Filter with Bayes Net has 0.99 of PRC which is maximum value than other models. The Color Layout Filter with Sequential Minimal Optimizer has 0.78 of PRC. This work governs the performances of all models but Fuzzy Opponent Histogram Filter with machine learning models have given best performances than Color Layout Filter techniques and also Bayes Net gives best outcome as well as less deviations compare than other Ada Boost and Sequential Minimal Optimizer.

Key Words: **Color Layout Filter, Wheat, Bayes Net, Fuzzy Opponent Histogram Filter, Wheat Leaf**

I Introduction

At now, wheat leaf diseases are identified through visual inspection. Manual experience is required, and the procedure is time-consuming and labor-intensive. Due to the wide variety of pests and unequal distribution of disease spots, it is challenging for specialists to undertake timely and accurate screening [1-3]. Consequently, precise disease severity estimation aids in wheat disease control and prevention. Less expensive inputs and less wasteful agricultural practises are two potential benefits [4].

Currently, the majority of early crop leaf disease feature extraction is accomplished manually. Despite the fact that the processes can classify the sick sections or leaves, they are frequently segmented. Initially, it increases labour costs and alters feature extraction algorithms for each illness type in a unique manner. Similar illnesses are difficult to distinguish apart. Traditional machine learning-based detection techniques rely primarily on feature extraction and need the building of unique recognition models for each crop disease, making them inflexible.

Individuals have experimented with a variety of machine vision applications for the identification of agricultural diseases and insect pests in recent years due to the rapid development of deep learning technologies. Conventional machine vision algorithms are predicated on the selection of pertinent features for a particular task and level of proficiency. The fundamental characteristics of the image are its hue, form, and texture. Every feature extractor was built by hand. The process is laborious and time-consuming. In addition, the feature extractors lack the ability to generalise. However, deep learning techniques can adjust the weight values and build an useful feature extractor by modifying the weight values. In terms of procedures, it is neither tedious nor time-consuming. The improved generalisation capabilities of the feature extractors allow them to successfully compensate for the deficiencies of standard machine vision approaches.

This research articles organizes, In section 2 presents that the literatures of related works; In section 3 governs that the terms and definition of this research work; In section 4 focuses results and interpretation of this research work; Finally section 5 shows that the conclusion of this research work.

II Literature Survey

Identification of crop diseases is a crucial aspect of agricultural production. It is an indispensable component of image processing. Nonetheless, it faces numerous obstacles, such as a complicated background , a high degree of similarity, and the segmentation of regions.[1-3]There are two types of methods for identifying crop diseases and pests. Elaraby et al. [1] suggested a deep-learning technique for recognising 25 distinct plant diseases. AlexNet, a deep convolutional neural model, obtained a 98.83% accuracy rate. It was more exact by 3.23 percentage points than a single AlexNet. Using a method based on principal component analysis, Atta et al. [4] accurately distinguished between healthy and diseased wheat leaf samples with 93.7% precision (PCA). Yin et al. [5] created DISE-Net, a new deep-learning network with a 97.12% accuracy rate for recognising maize diseases and pests. It is 2.87 percentage points more efficient than DenseNet12. As a result of the similar hue and texture of severity levels within the same class, fine-grained differences are minimal. Adapting traditional machine learning methods to severity estimate is hard [7]. Anitha et al. [8] built an unique deep convolutional neural network for disease classification of leaf smut, bacterial blight, and brown spot. The accuracy percentage for images of apple, rice, grape, and wheat leaf was 96.1 percent. Rimal et al. [9] The average accuracy of identification was 96.95%. Without deliberate design, data-driven deep learning can automatically acquire global features. Kumar et al. [10] created an adaptive Boosting SVM classifier for the identification of rice plant diseases, including bacterial leaf blight, brown spots, and leaf smut. It exhibited a sensitivity of up to 98.8 percent for recognising and diagnosing rice leaf diseases.[11] In agricultural disease and pest image processing and classification approaches, PCA and SVM are employed extensively.[12] The objective function of these approaches depends primarily on the Euclidean distance measure, which requires that the input sample space is isotropic. In a number of real-world applications, the isotropic assumption is false and does not accurately reflect the probable connection between the sample's dimensional components.[13-16]

As a result of the growth of artificial intelligence [14], image processing and classification research makes substantial use of deep learning techniques [15]. Dong et al. [14] suggested use a convolutionl neural network with differential amplification to identify wheat diseases. Its average identification accuracy increased by 6.03 percent compared to LeNet-5. Hridoy et al. [17] developed an enhanced convolutional neural network for the recognition of betel leaf rot and foot rot, achieving 96.02 percent accuracy using the Swish activation function on a test set of 1031 images. The accuracy of a conventional convolutional neural network was 6.49 percent lower than that of our system. Hridoy et al. [18] created an effective EfficientNet model for eight types of papaya diseases based on picture augmentation and transfer learning. Using Efficient Net B5, B6, and B7, the average accuracy of 6931 test images was 97.31 percent. Ali et al. [19] developed a unique technique termed feature fusion and PCA for accurately identifying 98.20% of agricultural diseases. Compared to ResNet50, the average accuracy has increased by 1.69 percentage points. Rahman et al. [20] proposed an image processing technique for the automatic identification and treatment of tomato leaf diseases based on a grey level co-occurrence matrix and support vector machine (SVM). For four types of leaf diseases affecting tomato plants, it showed an average accuracy of 92.5%. Gomez et al. [21] described a unique molecular approach based on loop-mediated isothermal amplification for identifying wheat pathogens. Although deep learning algorithms are capable of automatically extracting features, this is not always the case. They disregard the loss and separation of information on diverse feature types as the number of layers grows.[22] The majority of attributes, including colour, texture, and shape, are extracted without taking into account the bending and tilting of crop leaves, which could easily compromise the recognition impact.[24,27,28]. Zhang et al. [23] outlined an enhanced Ir-UNet technique for wheat yellow rust detection that incorporated an irregular encoder module, an irregular decoder module, and a content-aware channel re-weight module. It obtained the highest level of accuracy, 97.13 percent, surpassing UNet. Using an enhanced YOLOV3-Tiny model, Devisurya et al. [25] proposed a deep-learning technique for diagnosing turmeric leaf illnesses. Compared to YOLO-V2, it improved the F1 score by 8.9%. Bao et al. [26] developed a new technique for diagnosing wheat leaf diseases and severity based on elliptical-maximum margin criteria metric learning; it has an identification accuracy of 94.16 percent. Based on Inception-ResNet-v2 and VGG-16, Liu et al. [29] developed a system for identifying and categorising crop pests. On the IDADP dataset, it earned an average accuracy score of 97.71%. Jiang et al. [30] demonstrated multi-task deep transfer learning with Image NET for the recognition of rice and wheat leaf diseases with a 99.99% average accuracy.

III Terms and Definition

This section defines essential concepts from the Kaggle-downloaded wheat dataset utilised in this investigation. There are a total of 407 photographs in the collection, evenly distributed over three distinct categories. 102 are normal, 208 have stripe rust, and 97 have septoria out of the total. The photos were submitted to a range of machine learning techniques, including **Bayes Net**, **Sequential Minimal Optimizer , and AdaBoost**in order to develop the proposed model. The prosed system shows the borrowed data set apply for weka 3.9.5 at 10 fold cross validation for an optimal outcome.

Research Methodology:

- Fuzzy Opponent Histogram Filter with Bayes Net (FOHF+BN)
- Color Layout Filter with Bayes Net(CLF+BN)
- Fuzzy Opponent Histogram Filter with Sequential Minimal Optimizer(FOHF+SMO)
- Color Layout Filter with Sequential Minimal Optimizer(CLF+SMO)
- Fuzzy Opponent Histogram Filter with AdaBoostM1(FOHF+AdaBoost)
- Color Layout Filter with AdaBoostM1(CLF+AdaBoost)

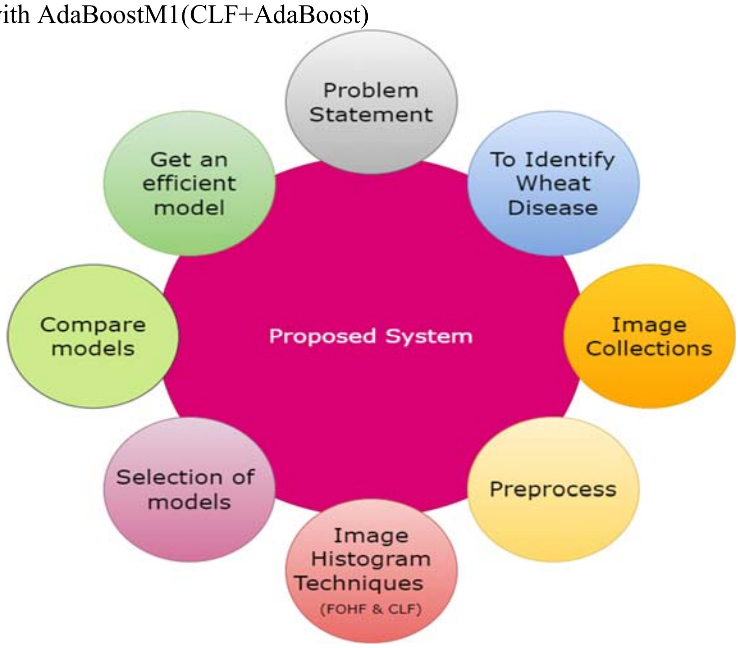

Figure 1: Proposed System

III Outcome and Interpretation

This section discusses with outcome of Fuzzy Opponent Histogram Filter with Bayes Net (FOHF+BN),Color Layout Filter with Bayes Net(CLF+BN),Fuzzy Opponent Histogram Filter with Sequential Minimal Optimizer(FOHF+SMO),Color Layout Filter with Sequential Minimal Optimizer(CLF+SMO),Fuzzy Opponent Histogram Filter with AdaBoostM1(FOHF+AdaBoost),and Color Layout Filter with AdaBoostM1(CLF+AdaBoost) of image histogram techniques with machine learning approaches. The below table shows that the various performance of selected classifiers.

Table 1: Performance of Selected models

S.No	Classifier	Accuracy	Precision	Recall
1	FOHF+BN	97%	0.97	0.97
2	CLF+BN	87%	0.87	0.87
3	FOHF+SMO	90%	0.92	0.90

4	CLF+SMO	83%	0.84	0.83
5	FOHF+AdaBoost	93%	0.94	0.93
6	CLF+AdaBoost	83%	0.84	0.83

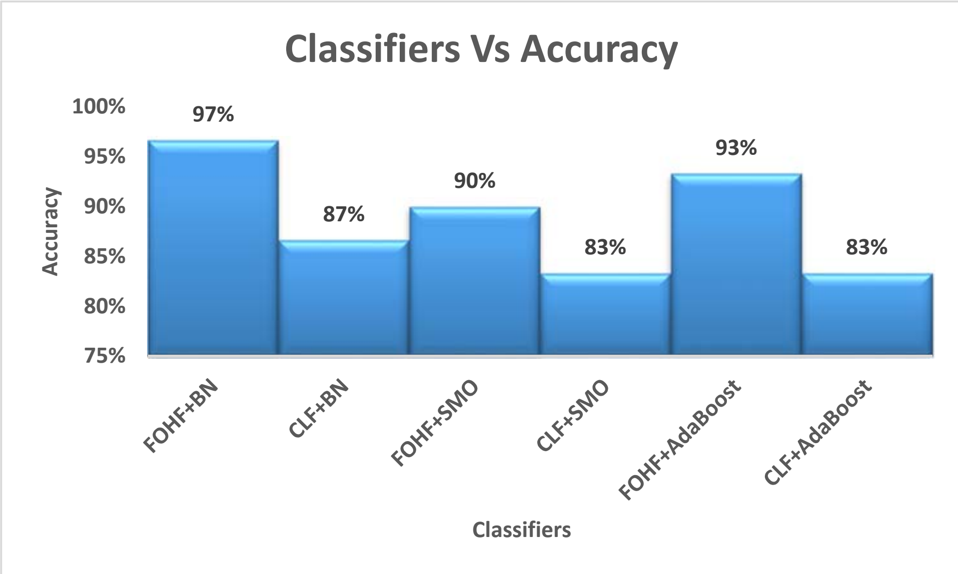

Figure 2: Selected Models Vs Accuracy

The figure 2 shows that the accuracy performance of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The FOHF+BN gives best outcome which is 97% of accuracy. The CLF+SMO and CLF+AdaBoost has same as well least outcome which is 83% of accuracy. The FOHF+AdaBoost has 93% of accuracy, FOHF+SMO has 90% of accuracy and CLF+BN has 87% of accuracy.

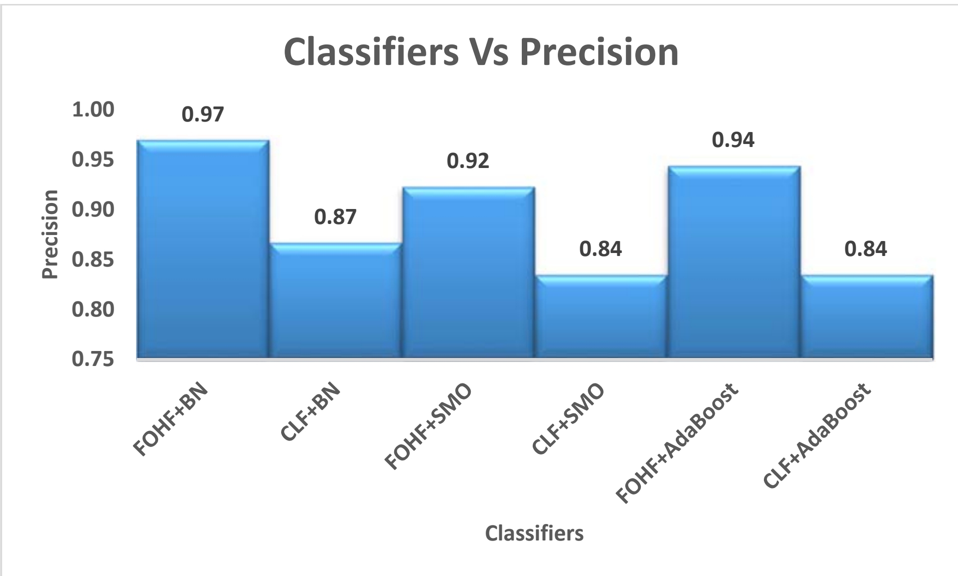

Figure 3: Selected Models Vs Precision

The figure 3 shows that the precision performance of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The FOHF+BN has 0.97 of precision which is best result than other models. The CLF+SMO and CLF+AdaBoost has 0.84 of precision which are least as well same outcome. The FOHF+AdaBoost has 0.94 of precision; the FOHF+SMO has 0.92 of precision; and the CLF+BN has 0.87 of precision

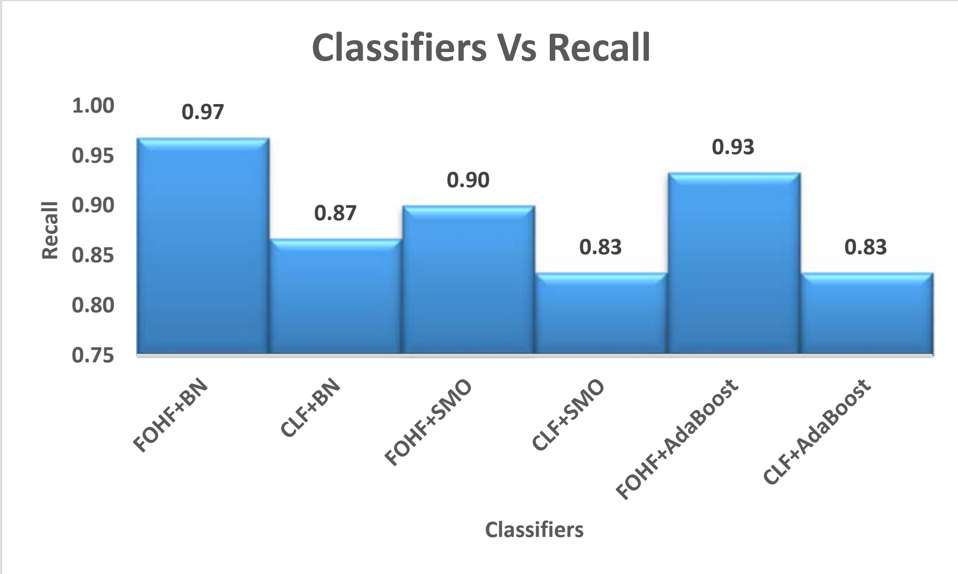

Figure 4: Selected Models Vs Recall

The figure 4 shows that the recall performance of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The FOHF+BN has 0.97 of recall which is best result than other models. The CLF+SMO and CLF+AdaBoost has 0.83 of recall which are least as well same outcome. The FOHF+AdaBoost has 0.93 of recall; the FOHF+SMO has 0.90 of recall; and the CLF+BN has 0.87 of recall.

Table 2: MCC,F-Measure and Kappa performance of selected models

S.No	Classifier	MCC	F-Measure	Kappa
1	FOHF+BN	0.95	0.97	0.95
2	CLF+BN	0.80	0.87	0.80
3	FOHF+SMO	0.86	0.90	0.85
4	CLF+SMO	0.75	0.83	0.75
5	FOHF+AdaBoost	0.91	0.94	0.90
6	CLF+AdaBoost	0.75	0.83	0.75

The above table 2 shows that the Matthews Correlation Coefficient (MCC), kappa statistic, F-Measure and values of Fuzzy Opponent Histogram Filter with Bayes Net (FOHF+BN),Color Layout Filter with Bayes Net(CLF+BN),Fuzzy Opponent Histogram Filter with Sequential Minimal Optimizer(FOHF+SMO),Color Layout Filter with Sequential Minimal Optimizer(CLF+SMO),Fuzzy Opponent Histogram Filter with AdaBoostM1(FOHF+AdaBoost),and Color Layout Filter with AdaBoostM1(CLF+AdaBoost) of image histogram techniques with machine learning approaches.

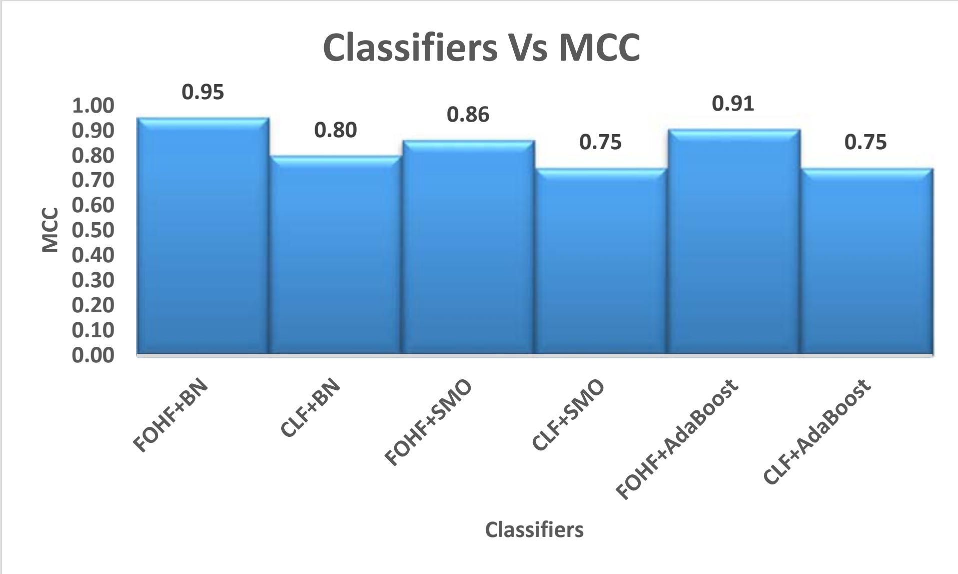

Figure 5: Selected Models Vs MCC

The figure 5 shows that the Matthews Correlation Coefficient (MCC) of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The CLF+SMO and CLF+AdaBoost has same as well as least outcome which is 0.75 of MCC. The FOHF+BN has best result which is 0.95 of MCC. The FOHF+AdaBoost has 0.91 of MCC; the FOHF+SMO has 0.86 of MCC; and the CLF+BN has 0.80 of MCC.

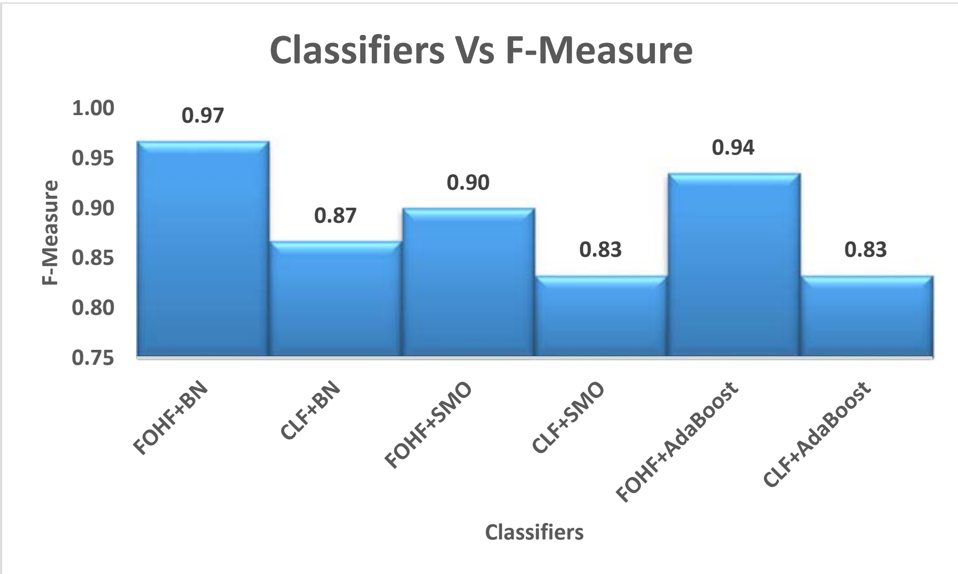

Figure 6: Selected Models Vs F-Measure

The figure 6 shows that the F- Measure performance of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The CLF+SMO and CLF+AdaBoost has same as well as least outcome which is 0.83 of F-Measure. The FOHF+BN has best result which is 0.97 of F-Measure. The FOHF+AdaBoost has 0.94 of F-Measure; the FOHF+SMO has 0.90 of F-Measure; and the CLF+BN has 0.87 of F-Measure.

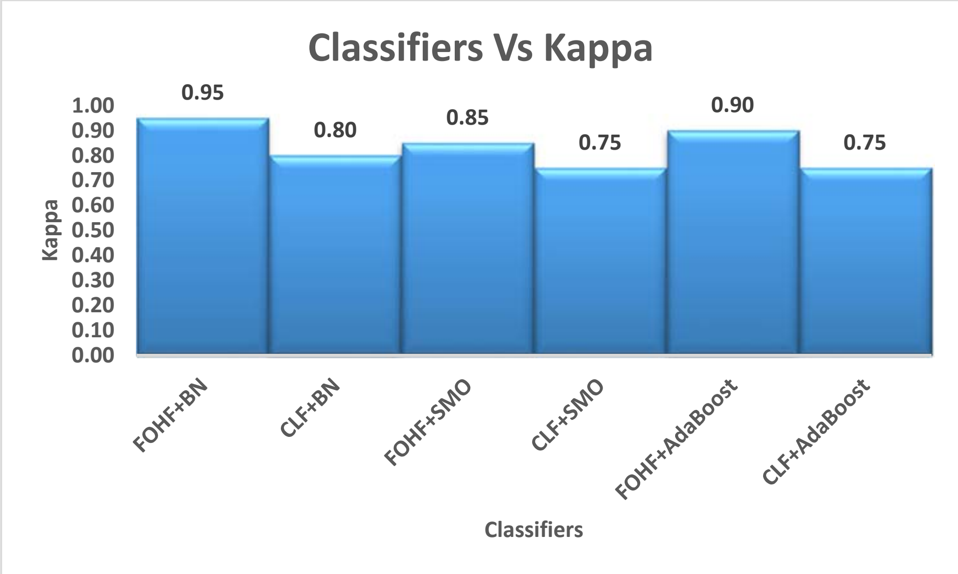

Figure 7: Selected Models Vs Kappa

The figure 7 shows that the Kappa performance of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The CLF+SMO and CLF+AdaBoost has same as well as least outcome which is 0.75 of Kappa. The FOHF+BN has best result which is 0.95 of Kappa value. The FOHF+AdaBoost has 0.90 of Kappa; the FOHF+SMO has 0.90 of F-Measure; and the CLF+BN has 0.87 of F-Measure.

Table 3: ROC and PRC performance of Selected Models

S.No	Classifier	Time	ROC	PRC
1	FOHF+BN	0.19	0.99	0.99
2	CLF+BN	0.05	0.98	0.97
3	FOHF+SMO	0.13	0.95	0.88
4	CLF+SMO	0.16	0.90	0.78
5	FOHF+AdaBoost	0.13	0.98	0.95
6	CLF+AdaBoost	0.05	0.96	0.95

The above table 3 shows that the performance of Time (In Sec.), Receiver Operating Characteristic Curve (ROC) and Precision Recall Curve (PRC) values of Fuzzy Opponent Histogram Filter with Bayes Net (FOHF+BN),Color Layout Filter with Bayes Net(CLF+BN),Fuzzy Opponent Histogram Filter with Sequential Minimal Optimizer(FOHF+SMO),Color Layout Filter with Sequential Minimal Optimizer(CLF+SMO),Fuzzy Opponent Histogram Filter with AdaBoostM1(FOHF+AdaBoost),and Color Layout Filter with AdaBoostM1(CLF+AdaBoost) models.

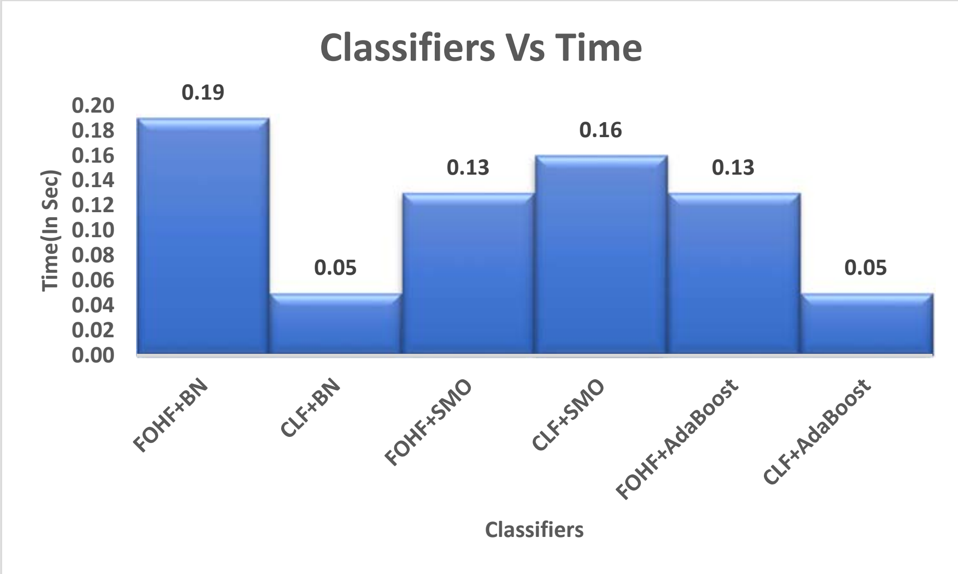

Figure 8: Selected Models Vs Time (In.Sec)

The above figure 8 represents that the time (In Sec.) performance of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The CLF+BN and CLF+AdaBoost takes same level of time consumption (0.05 seconds) as well least time for creating their models. The FOHF+BN takes more time for building its model. The FOHF+SMO and FOHF+AdaBoost has 0.05 for making their models and CLF+SMO takes 0.16 seconds for making its model.

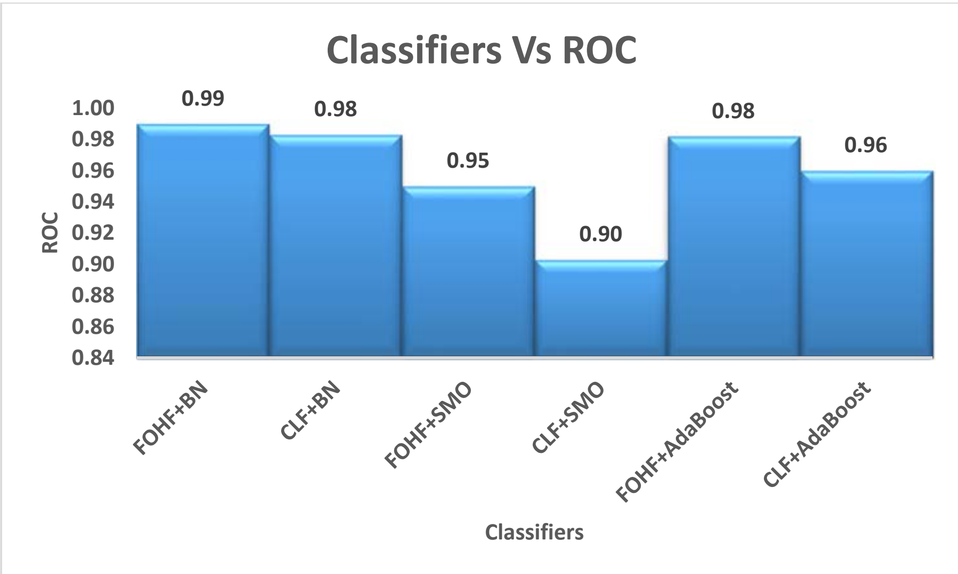

Figure 9: Selected Models Vs ROC

The figure 9 shows that the time (In Sec.) performance of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The FOHF+BN has highest ROC 0.99. The CLF+BN and FOHF+AdaBoost has 0.98 of ROC. The CLF+AdaBoost has 0.96 of ROC. The FOHF+SMO has 0.95 of ROC and CLF+SMO has 0.90 of ROC which is least value compare than other models.

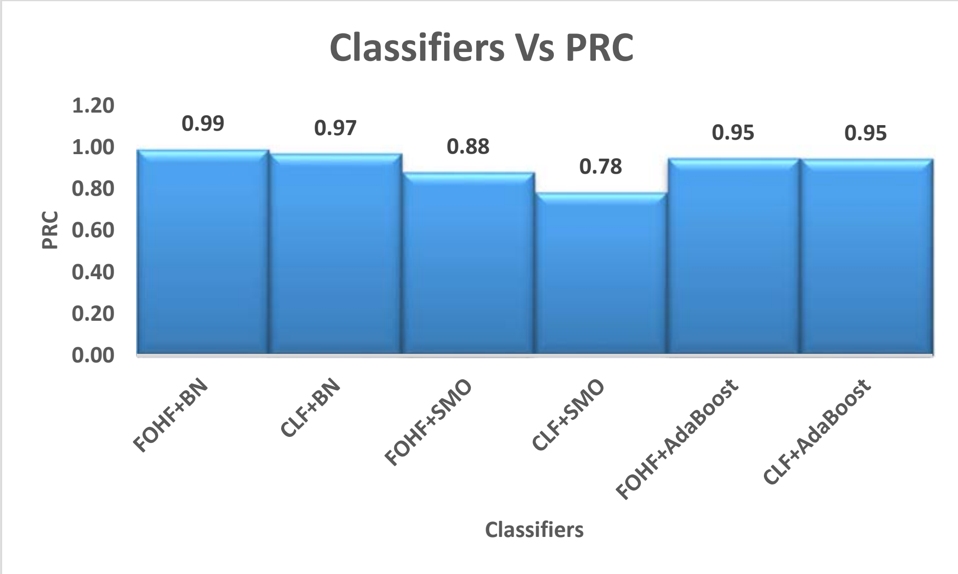

Figure 10: Selected Models Vs PRC

The figure 10 shows that the PRC performance of FOHF+BN, CLF+BN, FOHF+SMO, CLF+SMO, FOHF+AdaBoost, and CLF+AdaBoost models. The FOHF+BN has 0.99 of PRC which is maximum value than other models. The CLF+SMO has 0.78 of PRC. The CLF+BN has 0.97 of PRC. The FOHF+AdaBoost and CLF+AdaBoost has same value which is 0.95 of PRC and FOHF+SMO has 0.88 of PRC value.

Table 4: Deviation performance of Selected Models

S.No	Classifier	RAE	RRSE	MAE	RMSE
1	FOHF+BN	5.46%	31.51%	0.02	0.15
2	CLF+BN	18%	53.41%	0.08	0.25
3	FOHF+SMO	55%	65.82%	0.24	0.31
4	CLF+SMO	58.33%	70.71%	0.26	0.33
5	FOHF+AdaBoost	13.74%	45.93%	0.06	0.22
6	CLF+AdaBoost	27%	57.45%	0.12	0.27

The above table 4 shows that the deviation performance mean absolute error (MAE), root means squared error (RMSE), relative absolute error (RAE) and root relative squared error (RRSE) values of Fuzzy Opponent Histogram Filter with Bayes Net (FOHF+BN),Color Layout Filter with Bayes Net(CLF+BN),Fuzzy Opponent Histogram Filter with Sequential Minimal Optimizer(FOHF+SMO),Color Layout Filter with Sequential Minimal Optimizer(CLF+SMO),Fuzzy Opponent Histogram Filter with AdaBoostM1(FOHF+AdaBoost),and Color Layout Filter with AdaBoostM1(CLF+AdaBoost).

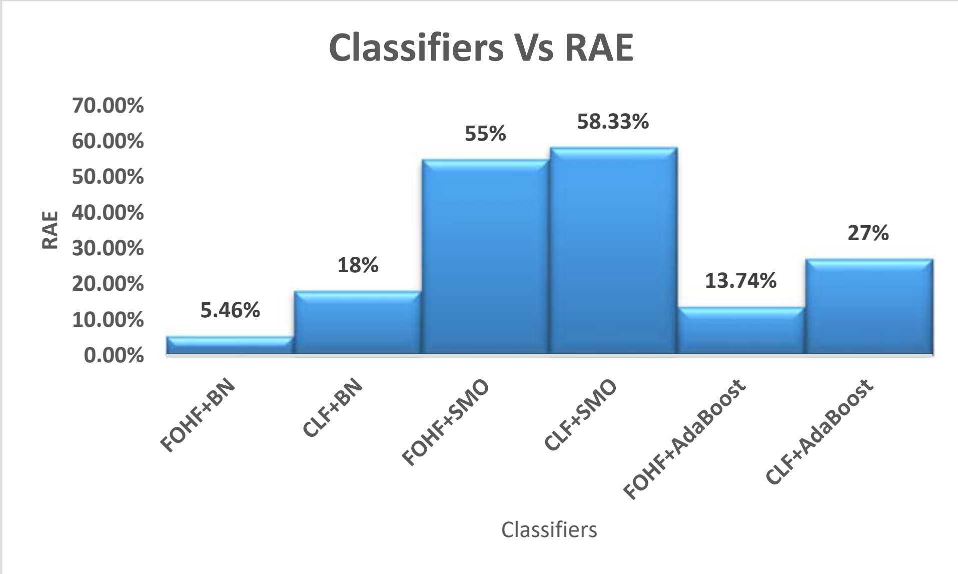

Figure 11: Selected Models Vs RAE

The FOHF+BN indicates a best performance of 5.46% of RAE, as shown in Diagram 11. 58.33% of RAE is the poorest performance of the CLF+SMO model. The FOHF+SMO has 55% of RAE, the CLF+AdaBoost has 27% of RAE, the CLF+BN has 18% of RAE, and the FOHF+AdaBoost has 13.74% of RAE, respectively.

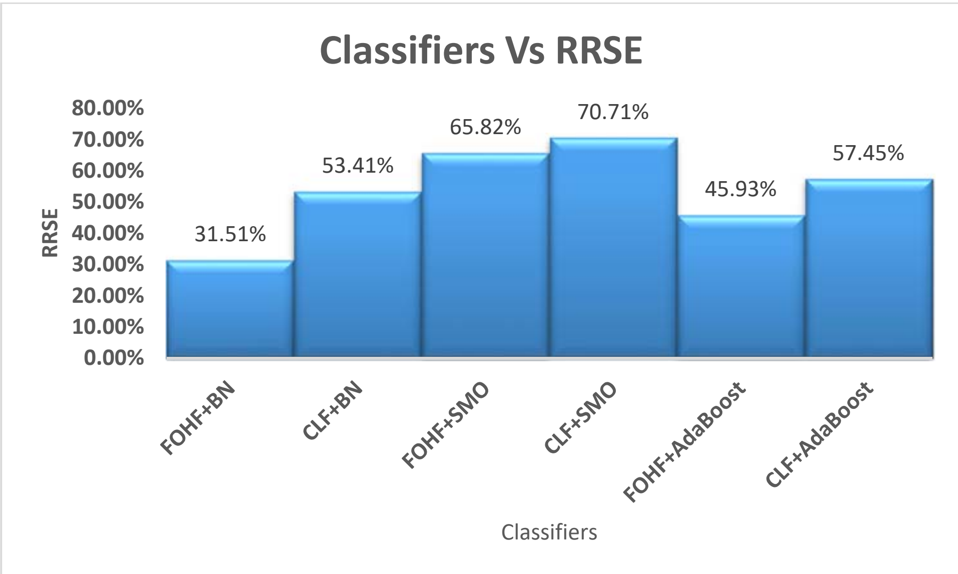

Figure 12: Selected Models Vs RRSE

The FOHF+BN indicates a best performance of 31.51% of RRSE, as shown in Diagram 12. 70.71% of RRSE is the poorest performance of the CLF+SMO model. The FOHF+SMO has 65.82% of RRSE, the CLF+AdaBoost has 57.45% of RRSE, the CLF+BN has 53.41% of RRSE, and the FOHF+AdaBoost has 45.93% of RRSE, respectively.

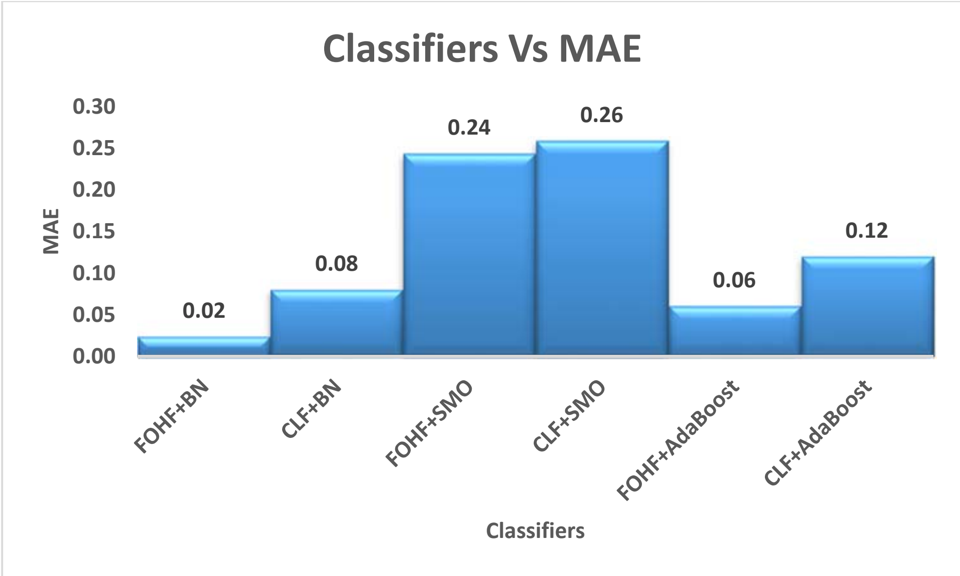

Figure 13: Selected Models Vs MAE

The FOHF+BN has the best performance, 0.02 of MAE, as depicted in diagram 11 above. The CLF+SMO has worst performance, 0.26 of MAE. The FOHF+SMO, CLF+AdaBoost, CLF+BN and FOHF+AdaBoost has 0.24 of MAE, 0.12 of MAE, 0.08 of MAE and 0.06 of MAE respectively.

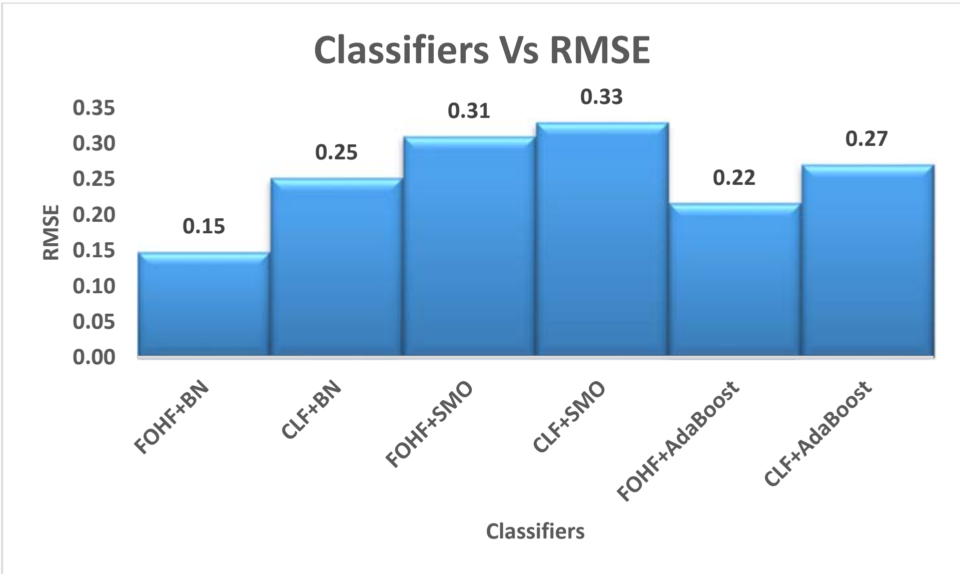

Figure 14: Selected Models Vs RMSE

The FOHF+BN has the best performance, 0.15 of RMSE, as depicted in diagram 12 above. The CLF+SMO has worst performance, 0.33 of RMSE. The FOHF+SMO, CLF+AdaBoost, CLF+BN and FOHF+AdaBoost has 0.31 of RMSE, 0.27 of RMSE, 0.25 of RMSE and 0.22 of RMSE respectively.

IV Conclusion

This study proposes a Bayes Net-based Fuzzy Opponent Histogram Filter, which outperforms existing models. With 97% accuracy, the Fuzzy Opponent Histogram Filter with Bayes Net is optimal. The Sequential Minimal Optimizer and Ada Boost Color Layout Filters both have 83% accuracy. The Fuzzy Opponent Histogram Filter with Bayes Net has 0.97 precision, besting other models. The Sequential Minimal Optimizer and Ada Boost Color Layout Filters have 0.84 precision and the same result. The Fuzzy Opponent Histogram Filter with BN has 0.97 recall, besting other models. The Sequential Minimal Optimizer and Ada Boost Color Layout Filters both have 0.83 recall. Color Layout Filter with Sequential Minimal Optimizer and Color Layout Filter with Ada Boost both have 0.75 MCC. With 0.95 MCC, the Fuzzy Opponent Histogram Filter with Bayes N performs best. The Sequential Minimal Optimizer and Ada Boost Color Layout Filters both yield 0.83 F-Measure. F-Measure 0.97 is optimum for the Fuzzy Opponent Histogram Filter with Bayes Net. Both Color Layout Filters with Sequential

Minimal Optimizer and Ada Boost have 0.75 Kappa. Kappa value 0.95 is optimum for the Fuzzy Opponent Histogram Filter with Bayes Net. The Fuzzy Opponent Histogram Filter with Bayes Net has ROC 0.99, whereas the Color Layout Filter with Sequential Minimal Optimizer has 0.90. Fuzzy Opponent Histogram Filter with Bayes Net has the highest PRC of 0.99. Color Layout Filter with Sequential Minimal Optimizer has 0.78 PRC. This work recommends that the Fuzzy Opponent Histogram Filter with machine learning models outperforms Color Layout Filter as well as Bayes Net gives best outcome than other learning patterns.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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