e-ISSN : 0976-5166
p-ISSN : 2231-3850

Deductive Learning for identifying COVID 19 by using Edge Histogram and Fuzzy Color and Texture Histogram Filter

S. M. Manimegalai [1], Dr.T.Ramaprabha [2]

[1]Research Scholar, PG and Research Department of Computer Science and Computer Application, Vivekanandha College of Arts and Science for Women (A), Elayampalayam- 637205. Tamil Nadu, India.

[2]Professor , PG and Research Department of Computer Science and Computer Application, Vivekanandha College of Arts and Science for Women (A), Elayampalayam- 637205. Tamil Nadu, India.

E-mail: megalaianand2@gmail.com[1], ramaradha1971@gmail.com[2]

Abstract:

The COVID-19 pandemic has attracted the attention of big data analysts and artificial intelligence engineers. This research focuses to identify the COVID -19 through machine learning algorithm by implementing Edge Histogram Filter and Fuzzy Color and Texture Histogram Filter techniques. This work reveals that Edge Histogram image equalization with Bayes Net of Bayes classification algorithm model has the highest accuracy (82.85%) compared to Edge Histogram with selected machine learning algorithms and FCTH image enhancement with selected machine learning algorithm models. Here, Edge Histogram image equalization with SMO algorithm model and FCTH image enhancement with selected machine learning algorithm models have the highest precision (0.83). Edge Histogram Filter with SMO algorithm model and Edge Histogram Filter with Random Forest algorithm model have 0.83 hit rates, the greatest recall compared to other Edge histogram and FCTH Filters. Edge Histogram Filter with Random Forest Model has the highest ROC value (0.96). Edge Histogram Filter using Random Forest model has the greatest PRC value. Due to measurement results, this system proposes Edge Histogram Filter with Random Forest. It outperforms existing methods for recognizing COVID 19 without wasting time on superfluous medical diagnoses.

Keywords: COVID19, Random Forest, Edge Histogram, FCTH Filter, Bayes Net

1 Introduction

COVID-19 has been shown to be contagious [7], and the World Health Organization (WHO) has proclaimed it a pandemic [1, 8]. Pneumonia is a highly transmissible illness caused by the SARS-CoV-2 infection, which emerged in December 2019 [1,-6]. COVID-19 causes a wide range of clinical symptoms, including fever, cough, and fatigue, and can lead to a fatal acute respiratory distress syndrome. As a result, the detection of risk factors and the development of precise prognostic prediction models are expected to advance clinical outcomes. In the event of a pandemic, early intervention and enhanced surveillance are critical. In recent years, computational intelligence technology has aided and achieved large emerging in a variety of medical and health sectors.[9-11] Machine learning (ML) is the subset of Artificial Intelligence has shown important clinical utility in the use of CT scan images to assist in the analysis of respiratory illnesses [12-14&38,39]. DL do an automatically detect features related to clinical results from CXR images. Recent research [15] has shown that using CXR scanning to build an AI system that can detect COVID-19.

The following is how the rest of the article is structured: Segment 2 depicts related works, whereas Segment 3 depicts materials and procedures. The discussions and results are accessible in Segment 4; lastly, in section 5, the conclusion is presented.

2 Literature Survey

This section focuses on the related works of this research work. This section concentrates on the study work's connected works. Researchers proposed system, an easy - to - interpret deep learning model, to make positive reasoning predictions. [16] Authors conducted a thorough assessment of recent deep learning algorithms for COVID-19 diagnosis. According to the research publications reviewed, the most prominent deep learning method for recognizing COVID-19 from medical images is Convolutional Neural Network (CNN). Haghanifar, A., et al. [18] demonstrated that simplistic models, like the vast majority of pre - trained models networks in the literature, focus on unlabeled data for decision-making. Lin Yang et al. [19] suggested three architectures, F-EDNC, FC-EDNC, and O-EDNC, to detect COVID-19 infections from chest computed tomography (CT) images rapidly and accurately. Mask R-CNN has been trained to detect and localize two types of lesions in images. These detections have been fused in the second stage to classify the entire input images[25,26]. B. Arulanandam et al. [27] discovered that public policy regulations can be effectively aligned with global health priorities'. Pandey et al. [28] aided in the identification of an excellent mix of deep learning, natural language processing, and diagnostic imaging to improve diagnosis. D. Müller et al. [29] proposed a novel automated segmentation workflow for COVID-19 diseased regions that can manage small datasets by using variant databases.D.I. Mors et al.[30] proposed an improvement in COVID-19 screening performance by utilizing several cycle generative adversarial networks to create important and informative synthetic images to address the lack of COVID-19 samples. In the context of low-quality, low-detail sets of data procured from mobile devices D.L. Fung et al.[31] developed a single 2 different deep learning model to segment COVID19 lesions from chest CT images to aid in the rapid diagnosis of COVID-19. D. Singh et al. [32] created and used a deep convolutional neural network (CNN). Furthermore, CNN hyper-parameters have been tuned utilizing Multi-objective Adaptive Differential Evolution (MADE). The proposed DUDA-Net approach by F. Xie et al.[33] can automatically segment COVID-19 lesions with impressive performance, indicating that the proposed method has significant clinical significance.

3 Materials and Methods

This segment emphases on the study work's materials and methods. The dataset Covid19 images was acquired from the Kaggle repository.[34,35,37] The below table shows that the description of the borrowed dataset.

Table 1: Meta data of Dataset

S.No	Category	Actual Images	10 % of Sample Size
1	Covid19	3616	362
2	Viral Pneumonia	1345	135
3	Lung Opacity	6012	601
4	Normal	10192	1019

Methods:

The subsequent approaches are applied in this work.[35,36,37]

1) Image Collections
2) Preprocessing
3) Apply Edge Histogram and Fuzzy Color and Texture Histogram Filter
4) Apply for learning algorithms {Bayes Net(BN), Sequential Minimal Optimization, Instance Based classifier(KNN), Bagging, JRip, Random Forest(RF)}
5) To get efficient outcome
6) Find an Optimal model

To produce an efficient result, these strategies were applied in one of the leading open source software namely, Weka 3.9.5. This study uses only 10% of the total dataset and uses 10 fold cross validation for all categories.

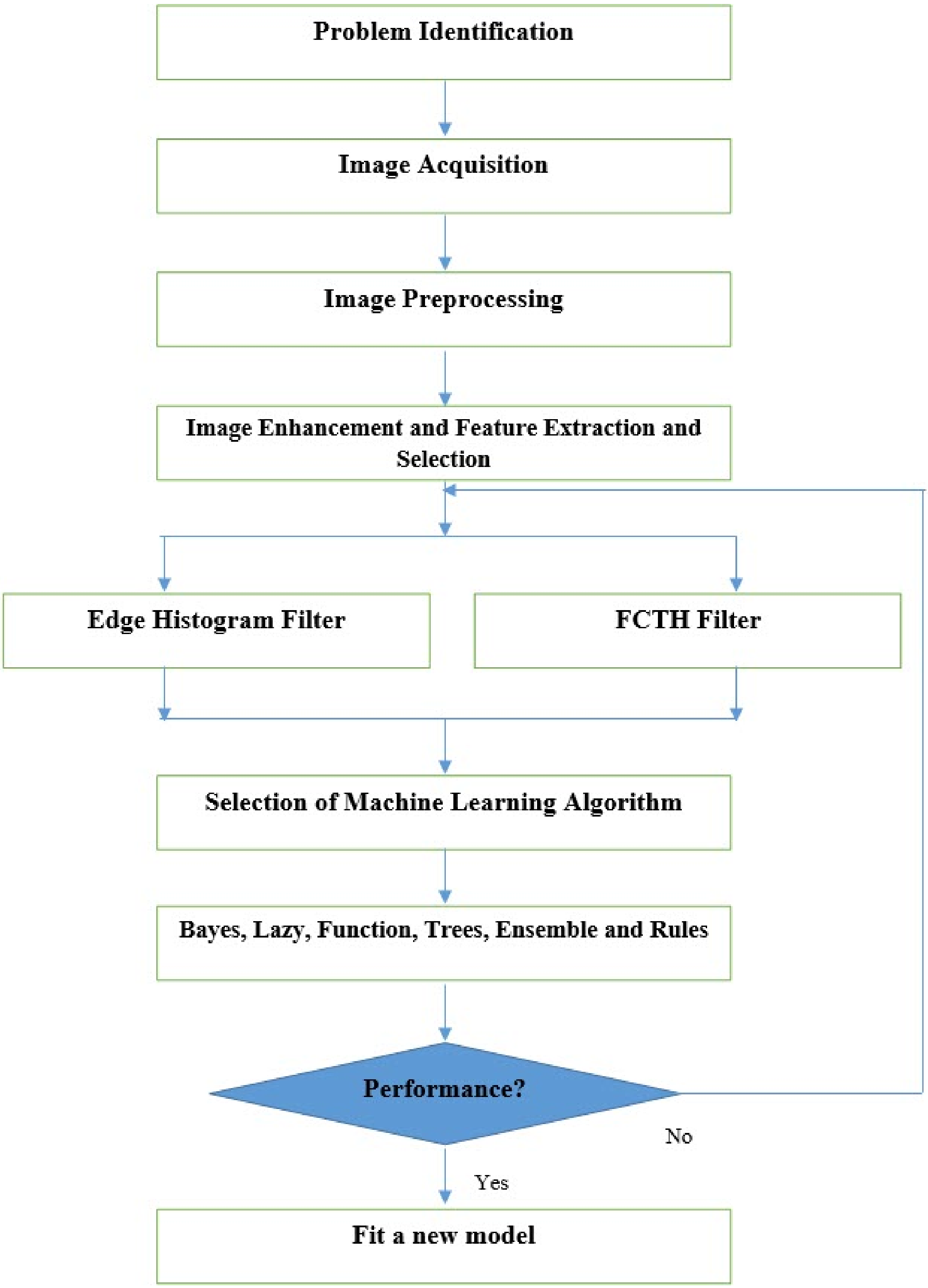

Figure 1: Proposed System

4 Results and Discussions

This section focuses on the results and discussion of this work. Selected algorithms by using image histogram techniques are used to find out an efficient outcome.

Table 2: Performance of various Machine Learning Algorithms by using Edge Histogram and Fuzzy Color and Texture Histogram Filter

S.No	Filter	Category	Algorithm	Accuracy	Precision	Recall	ROC	PRC	Time Taken to build model (In Seconds)
1	Edge Histogram	Bayes	Bayes Net	77.61%	0.78	0.78	0.94	0.83	0.08
2	FCTH Filter	Bayes	Bayes Net	64.15%	0.70	0.64	0.85	0.69	0.11
3	Edge Histogram	Functions	SMO	82.85%	0.83	0.83	0.92	0.78	0.83
4	FCTH Filter	Bayes	SMO	66.08%	0.79	0.66	0.79	0.58	0.67
5	Edge Histogram	Lazy	IBK	80.30%	0.8	0.8	0.86	0.71	0.00
6	FCTH Filter	Bayes	IBK	65.04%	0.63	0.65	0.84	0.69	0.00
7	Edge Histogram	Ensemble	Bagging	79.40%	0.79	0.79	0.94	0.84	0.89
8	FCTH Filter	Bayes	Bagging	67.60%	0.66	0.68	0.86	0.72	2.67
9	Edge Histogram	Rules	Jrip	73.36%	0.73	0.73	0.85	0.66	3.55
10	FCTH Filter	Bayes	Jrip	65.56%	0.63	0.66	0.84	0.69	3.78
11	Edge Histogram	Trees	Random Forest	82.43%	0.84	0.83	0.96	0.89	1.39
12	FCTH Filter	Bayes	Random Forest	66.56%	0.65	0.67	0.85	0.71	8.8

The above Table 2 shows that the performance of selected machine learning algorithm by using image enhancement technique on borrowed data.

The Bayes Net algorithm is producing 77.61% of accuracy level while implementing Edge Histogram Filter of image equalization technique, the Bayes Net algorithm is having 64.15% of accuracy level when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique, the SMO algorithm is producing 82.85% of accuracy level while implementing Edge Histogram Filter of image equalization technique, the SMO algorithm is having 66.08% of accuracy level when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique, the Instance Based Algorithm is producing 80.30% of accuracy level while implementing Edge Histogram Filter of image equalization technique, the Instance Based Algorithm is having 65.04% of accuracy level when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique, the Bagging algorithm is producing 79.40% of accuracy level while implementing Edge Histogram Filter of image equalization technique, the Bagging algorithm is having 67.60% of accuracy level when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique, the Jrip algorithm is producing 73.36% of accuracy level while implementing Edge Histogram Filter of image equalization technique, the Jrip algorithm is having 65.56% of accuracy level when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique , the Random Forest algorithm is producing 82.43% of accuracy level while implementing Edge Histogram Filter of image equalization technique and the

Random Forest algorithm is having 66.56% of accuracy level when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique.

The Bayes Net algorithm is yielding 0.78 of precision while implementing Edge Histogram Filter of image equalization technique, the Bayes Net algorithm is holding 0.70 of precision when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique, the SMO algorithm is yielding 0.83 of precision while implementing Edge Histogram Filter of image equalization technique, the SMO algorithm is holding 0.79 of precision when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique, the Instance Based Algorithm is yielding 0.80 of precision while implementing Edge Histogram Filter of image equalization technique, the Instance Based Algorithm is holding 0.63 of precision when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique, the Bagging algorithm is yielding 0.79 of precision while implementing Edge Histogram Filter of image equalization technique, the Bagging algorithm is holding 0.66 of precision when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique, the Jrip algorithm is yielding 0.73 of precision, the Jrip algorithm is holding 0.63 of precision when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique and Random Forest algorithm is yielding 0.84 of precision while implementing Edge Histogram Filter of image equalization technique and the Random Forest algorithm is holding 0.65 of precision when apply Fuzzy Color and Texture Histogram Filter of image feature extraction technique.

The Bayes Net algorithm is cropping 0.78 of Recall while applying Edge Histogram Filter for making image histogram , the Bayes Net algorithm is harvesting 0.64 of Recall when using Fuzzy Color and Texture Histogram Filter, the SMO algorithm is cropping 0.83 of Recall while applying Edge Histogram Filter for making image histogram, the SMO algorithm is harvesting 0.66 of Recall when using Fuzzy Color and Texture Histogram Filter, the Instance Based Algorithm is cropping 0.80 of Recall while applying Edge Histogram Filter for making image histogram, the Instance Based Algorithm is harvesting 0.65 of Recall when using Fuzzy Color and Texture Histogram Filter, the Bagging algorithm is cropping 0.79 of Recall while applying Edge Histogram Filter for making image histogram, the Bagging algorithm is harvesting 0.68 of Recall when using Fuzzy Color and Texture Histogram Filter, The Jrip algorithm is cropping 0.73 of Recall while applying Edge Histogram Filter for making image histogram, the Jrip algorithm is harvesting 0.66 of Recall when using Fuzzy Color and Texture Histogram Filter, the Random Forest algorithm is cropping 0.83 of Recall while applying Edge Histogram Filter for making image histogram and the Random Forest algorithm is harvesting 0.67 of Recall when using Fuzzy Color and Texture Histogram Filter.

The Bayes Net algorithm is gaining 0.94 of receiver operating characteristic curve (ROC) value while utilizing Edge Histogram Filter of image enhancement technique , The Bayes Net algorithm of Bayes category is showing 0.85 of ROC while adopting Fuzzy Color and Texture Histogram Filter, The Sequential Minimal Algorithm of function category is gaining 0.92 of ROC while utilizing Edge Histogram Filter of image enhancement technique, the Sequential Minimal Algorithm of function category is showing 0.79 of ROC while adopting Fuzzy Color and Texture Histogram Filter, the Instance Based algorithm of Lazy category is gaining 0.86 of ROC while utilizing Edge Histogram Filter of image enhancement technique, the Instance Based algorithm of Lazy category is showing 0.84 of ROC while adopting Fuzzy Color and Texture Histogram Filter, the Bagging algorithm of ensemble category is gaining 0.94 of ROC while utilizing Edge Histogram Filter of image enhancement technique, the Bagging algorithm of ensemble category is showing 0.86 of ROC while adopting Fuzzy Color and Texture Histogram Filter, the Jrip algorithm of Rules category is gaining 0.85 of ROC while utilizing Edge Histogram Filter of image enhancement technique, the Jrip algorithm of Rules category is showing 0.84 of ROC while adopting Fuzzy Color and Texture Histogram Filter, the Random Forest algorithm of tree category is gaining 0.96 of ROC while utilizing Edge Histogram Filter of image enhancement technique, and the Random Forest algorithm of tree category is showing 0.85 of ROC value while adopting Fuzzy Color and Texture Histogram Filter.

The Bayes Net algorithm is having 0.83 of PRC value by using Edge Histogram Filter for making image histogram, the Bayes Net algorithm is having 0.69 of PRC value by implementing Fuzzy Color and Texture Histogram Filter technique, the SMO algorithm is having 0.78 of PRC value by using Edge Histogram Filter for making image histogram, the SMO algorithm is having 0.58 of PRC value by implementing Fuzzy Color and Texture Histogram Filter technique, the Instance Based Algorithm is having 0.71 of PRC value by using Edge Histogram Filter for making image histogram, the Instance Based Algorithm is having 0.69 of PRC value by implementing Fuzzy Color and Texture Histogram Filter technique, the Bagging algorithm is having 0.84 of PRC value by using Edge Histogram Filter for making image histogram, the Bagging algorithm is having 0.72 of PRC value by implementing Fuzzy Color and Texture Histogram Filter technique, the Jrip algorithm is having 0.66 of PRC value, the Jrip algorithm is having 0.69 of PRC value by implementing Fuzzy

Color and Texture Histogram Filter technique, the Random Forest algorithm is having 0.89 of PRC value by using Edge Histogram Filter for making image histogram and the Random Forest algorithm is having 0.71 of PRC value by implementing Fuzzy Color and Texture Histogram Filter technique.

When using Edge Histogram Filter, the Bayes Net algorithm builds a model in 0.08 seconds. When using the Fuzzy Color and Texture Histogram Filter technique, the Bayes Net algorithm builds a model in 0.11 seconds. When using the SMO algorithm, the model is built in 0.83 seconds when using Edge Histogram Filter and in 0.67 seconds when using the Fuzzy Color and Texture Histogram Filter technique. The Bagging algorithm takes 0.89 seconds to build a model, the Bagging algorithm takes 2.67 seconds to build a model by implementing the Fuzzy Color and Texture Histogram Filter technique, and the Jrip algorithm takes 3.55 seco to build a model. The Instance Based Algorithm takes zero seconds to build a model when applying the Edge Histogram Filter, the Instance Based Algorithm takes zero seconds to build a model by implementing the FCTH.

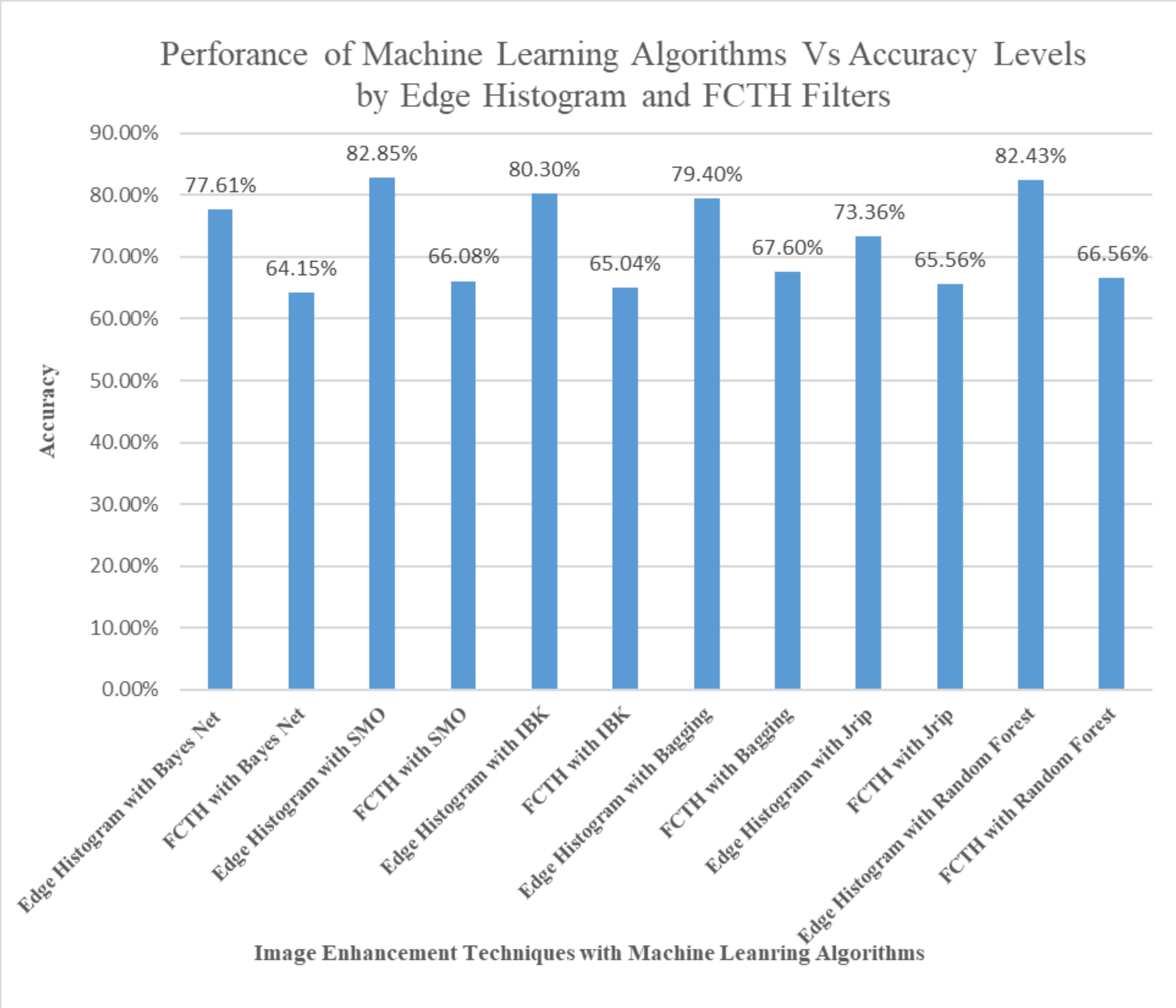

Figure 2: Accuracy performance of Edge Histogram Filter and FCTH Filter by selected learning approaches

The above diagram 2 shows that the Performance of Accuracy levels on machine learning algorithms by using Edge Histogram Filter and FCTH Filter. By applying Edge Histogram Filter, the least accuracy level is 75.11% of accuracy which is produced by Bayes Net of Bayes Classification category algorithm compare with other models. The maximum accuracy level is 82.52% of level of accuracy which is produced by Random Forest classification algorithm. The Bagging classification algorithm, K Nearest Neighborhood classification algorithm, Sequential Minimal Optimization classification algorithm, and Jrip classification algorithm are having 76% of accuracy level to 78.27% of accuracy level. Such as Bagging algorithm is having 78.27% of accuracy level, IBK is having 78.03% of accuracy level, SMO is having 76.15% of accuracy level and Jrip classification algorithm is 76% of accuracy level.

By using FCTH Filter, the least accuracy level is 64.15% of accuracy which is produced by Bayes Net of Bayes Classification category algorithm compare with other models. The maximum accuracy level is 66.56% of level of accuracy which is produced by Random Forest classification algorithm. The Bagging classification algorithm, Sequential Minimal Optimization classification algorithm, Jrip classification algorithm and K Nearest Neighborhood classification algorithm, are having 65.04% of accuracy level to 66.08% of accuracy level. Such as IBK is having 65.04% of accuracy level, Jrip classification algorithm is 65.56% of accuracy level SMO is having 66.08% of accuracy level and Bagging algorithm is having 67.60% of accuracy level.Actually, The Edge Histogram of image enhancement technique with several machine learning classification models are cropping from 73.36% of accuracy level to 82.85% of accuracy level. The FCTH image enhancement is showing from 64.15% of accuracy level to 67.60% of accuracy level. In generally, Edge Histogram enhancement gives better result compare with FCTH filter technique for borrowed dataset.

The leading accuracy level is 82.85% which is owned by Edge Histogram image equalization technique with Bayes Net of Bayes classification algorithm model compare with other Edge Histogram with selected machine learning algorithms and the FCTH image enhancement technique with selected machine learning algorithm models. The least accuracy value is 64.15% which is kept by FCTH with Bayes Net of Bayes Classification algorithm model compare with other Edge Histogram with selected machine learning algorithms and t FCTH image enhancement technique with selected machine learning algorithm models.

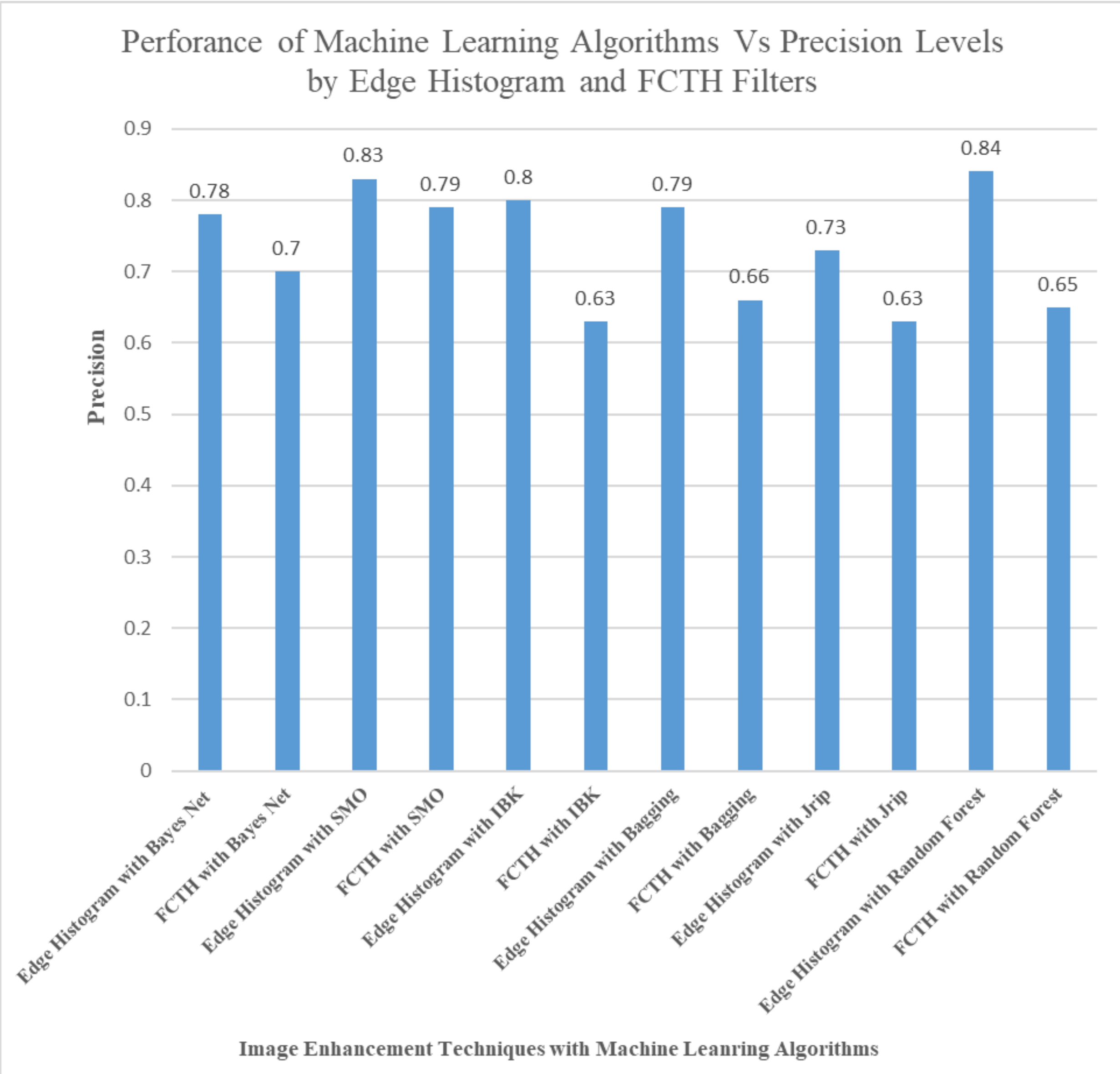

Figure 3: Precision performance of Edge Histogram Filter and FCTH Filter by selected learning approaches

The above diagram 3 shows that the Performance of Precision (precision) levels on machine learning algorithms by using Edge Histogram Filter and FCTH Filter. By using Edge Histogram image enhancement technique, the least precision is produced by Jrip classification algorithm which is cropping 0.73 of precision value compare with other models. The highest precision compare with other models is 0.84 which is produced by Random Forest classification algorithm. The Sequential Minimal Optimization classification algorithm and the K Nearest Neighborhood classification algorithm such as Instance Based Classification algorithm are cropping 0.83 of precision and 0.80 of precision. The Bagging classification algorithm of ensemble classification category is cropping 0.79 of precision and Bayes Net classification algorithm is cropping 0.78 of precision.

By applying the FCTH of image equalization technique, the least positive predictive value is owned by Jrip classification algorithm and IBK algorithm are having same precision value which is cropping 0.63 of positive predictive value compare with other models. The highest precision value compare with other models is 0.79 which is owned by SMO classification algorithm. The Random Forest, Bagging, and Bayes Net classification algorithms are cropping from 0.65 of precision to 0.70 of precision. Such as Random Forest is having 0.65 of precision. The Bagging classification algorithm is cropping 0.66 of precision and Bayes Net algorithm is cropping 0.70 of precision.

In reality, the precision level of The Edge Histogram, an image enhancement technique, is increasing from 0.73 to 0.83 when used with specific machine learning classification models. Using specific machine learning methods, the FCTH picture enhancement methodology produces results with precision levels ranging from 0.63 to 0.79.

In comparison to other Edge Histograms with chosen machine learning algorithms and FCTH image enhancement technique with chosen machine learning algorithm models, the leading precision level is 0.83, which is owned by Edge Histogram image equalization technique with Sequential Minimal Optimization algorithm model. There are two models, and their combined precision is 0.63. Compared to other Edge Histogram with selected machine learning algorithms and the FCTH image improvement technique with selected machine learning algorithm models, FCTH with Instance Based Clarification algorithm model and FCTG with Jrip algorithm model are providing the least precision value. In comparison to the FCTH filter technique, the Edge Histogram improvement produces better results with the borrowed dataset.

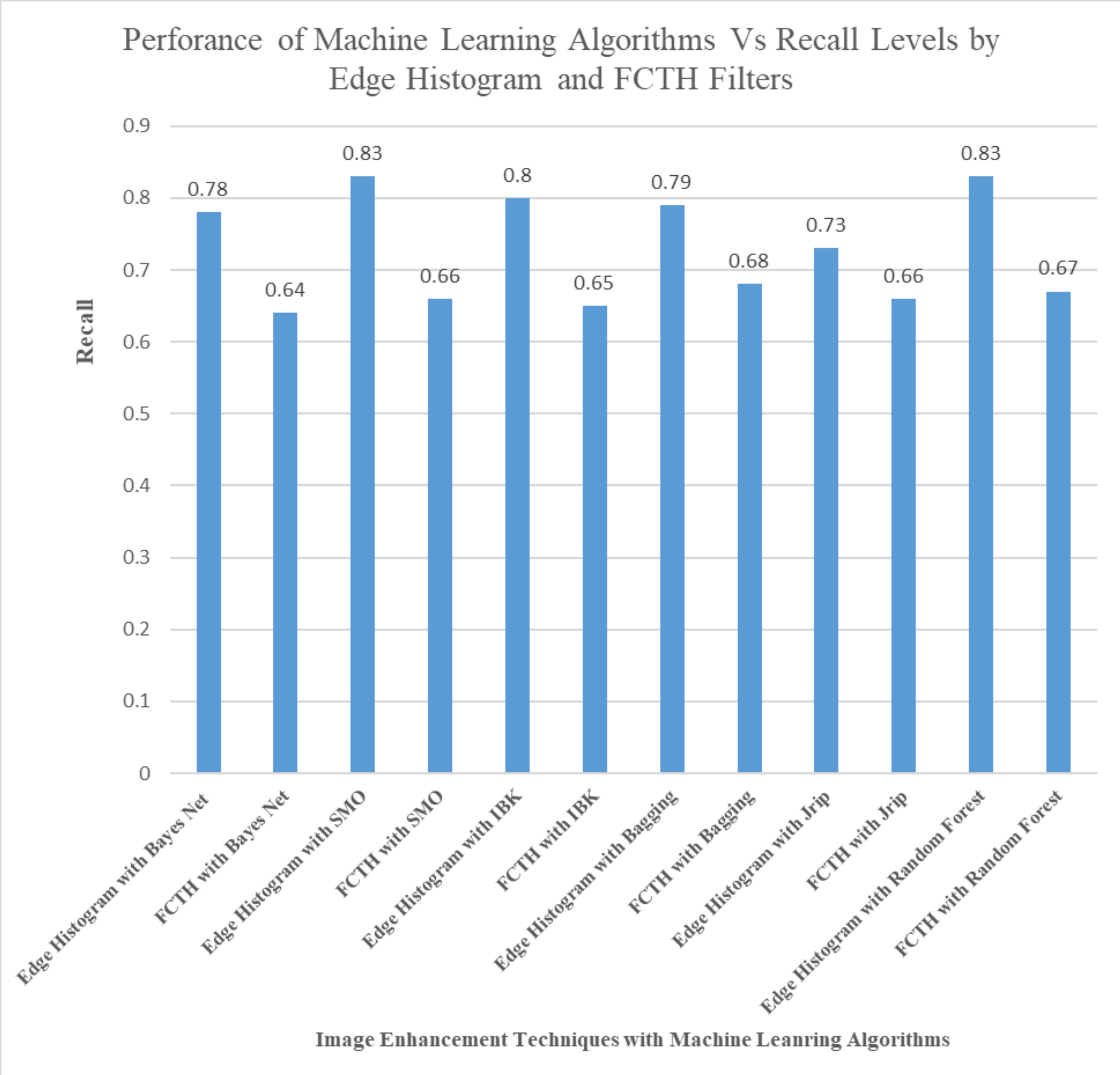

Figure 4: Recall performance of Edge Histogram Filter and FCTH Filter by selected learning approaches

The above diagram 4 shows that the Performance of Recall levels on machine learning algorithms by using Edge Histogram Filter and FCTH Filter.

While applying the Edge Histogram Filter, the Jrip classification algorithm is having 0.73 of recall which is lowest Recall compare with other models. The Random Forest Classification algorithm is having 0.83 of recall which is highest precision value compare than other models. The Bayes Net classification algorithm of Bayes category, Bagging algorithm of ensemble category, Instance Based classification algorithm of Lazy classification category, and Sequential Minimal Optimization of function classification category are having recall from 0.78 of Recall to 0.83 of recall. Such as The Bayes Net classification algorithm of Bayes category is having 0.78 of recall, Bagging algorithm of ensemble category is having 0.79 of recall, Instance Based classification algorithm of Lazy classification category is having 0.80 of recall, Sequential Minimal Optimization of function classification category is having 0.83 of recall.

While using the FCTH Filter, that the IBK classification algorithm is having 0.64 of recall which is lowest Recall compare with other models. The Bagging Classification algorithm is having 0.68 of recall which is highest precision value compare than other models. The Instance Based classification algorithm of Lazy classification category, Sequential Minimal Optimization of function classification category, the Jrip classification algorithm of Rules classification category and Random Forest of Tree classification category are having recall from 0.65 of recall to 0.67 of recall. Such as IBK is having 0.65 of Recall, SMO and Jrip classification are holding same Recall which is 0.66 of recall and Random Forest is holding 0.67 of Recall.

In reality, the cropping range for The Edge Histogram of image improvement technique with chosen machine learning algorithms is 0.73 to 0.83. The FCTH picture enhancement is increasing the recall from 0.64 to 0.68.

In comparison to other Edge Histogram and FCTH Filter with other chosen machine learning algorithms, the Edge Histogram Filter with Sequential Minimal Optimization algorithm model and Edge Histogram Filter with Random Forest method model are displaying 0.83 percent hit rates, which is the highest recall. The Bayes Net model coupled with the FCTH Filter produces the least recall (0.64). For borrowed datasets, Edge Histogram augmentation typically produces better results than FCTH filtering.

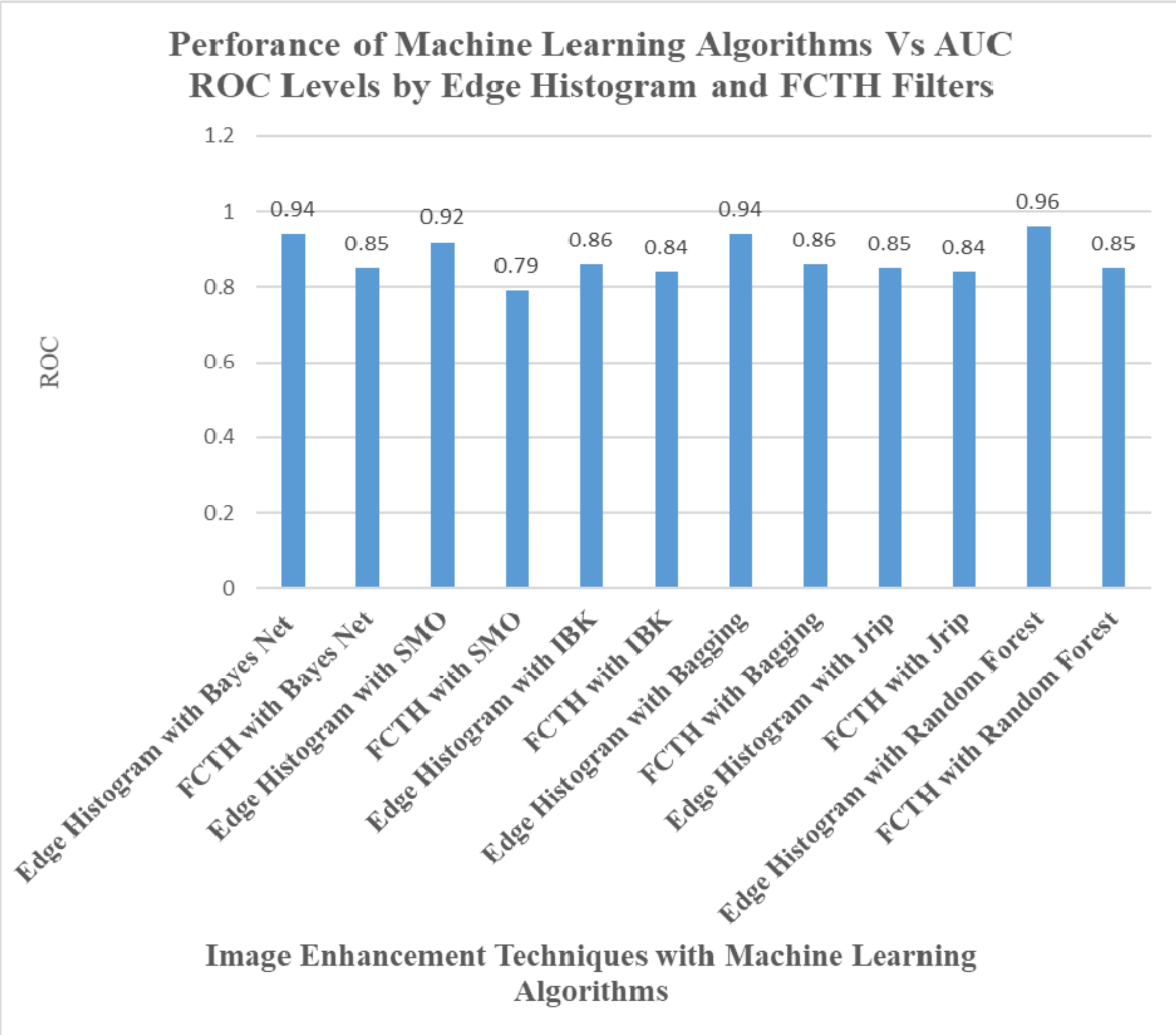

Figure 5: ROC performance of Edge Histogram Filter and FCTH Filter by selected learning approaches

The above diagram 5 shows that the Performance of ROC levels on machine learning algorithms by using Edge Histogram Filter and FCTH Filter.

In Edge Histogram Filter, the Jrip classification algorithm is showing the least ROC value which is 0.85 of ROC value. The leading ROC value is produced by Random Forest Classifier which is 0.96 of ROC value. The IBK classifier algorithm, Sequential Minimal Optimization classification algorithm, Bayes Net classification algorithm, and Bagging classification algorithm are holding the ROC values from 0.86 to 0.94 of ROC value. Such as, the IBK classification algorithm is holding 0.86 of ROC value, Sequential Minimal Optimization classification algorithm is holding 0.92 of ROC value, Bayes Net classification algorithm is holding 0.94 of ROC value, and Bagging classification algorithm is holding 0.94 of ROC value.

In FCTH Filter, the SMO classification algorithm is showing the least ROC value which is 0.79 of ROC value. The leading ROC value is produced by Bagging Classifier which is 0.86 of ROC value. The IBK classifier algorithm, Jrip classification algorithm, Bayes Net classification algorithm, and Random Forest classification algorithm are holding the ROC values from 0.84to 0.85 of ROC value. Such as the IBK classification algorithm and Jrip classification algorithm are holding 0.86 of ROC value, Bayes Net classification algorithm and Random Forest algorithm are holding 0.85 of ROC value.

The Edge Histogram of image enhancement technique with selected machine learning classification models are cropping ROC values between 0.85 of ROC and 0.96 of ROC value. The FCTH image enhancement technique with selected machine learning algorithm is showing from 0.79 of ROC value to 0.86 of ROC value.

The Edge Histogram Filter with Random Forest Model is yielding highest ROC value among all the selected models which is 0.96 of ROC value. The FCTH Filter with SMO model is producing least ROC value among the model which is 0.79 of ROC value. In generally, The Edge Histogram enhancement gives better result compare with FCTH filter technique by applying selected machine learning algorithms for borrowed dataset.

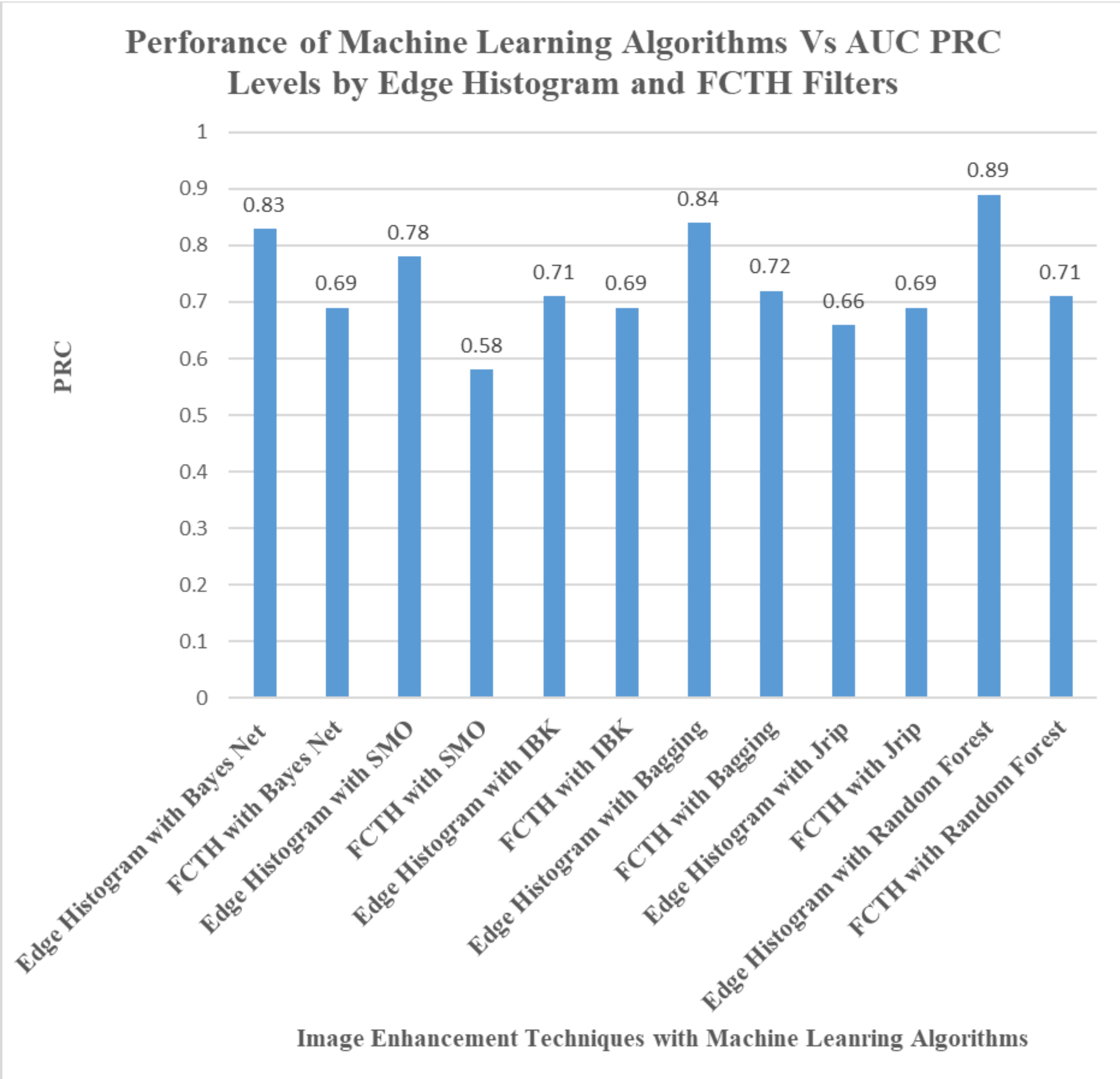

Figure 6: PRC performance of Edge Histogram Filter and FCTH Filter by selected learning approaches

The above diagram 6 shows that the Performance of PRC levels on machine learning algorithms by using Edge Histogram Filter and FCTH Filter.

In Edge Histogram Filter, the Jrip classification algorithm is showing the least PRC value which is 0.66. The leading PRC value is produced by Random Forest Classifier which is 0.89. The IBK classifier algorithm, Sequential Minimal Optimization classification algorithm, Bayes Net classification algorithm, and Bagging classification algorithm are holding the PRC values from 0.71 to 0.84. Such as The Jrip classification algorithm is holding 0.86 of PRC value, Sequential Minimal Optimization classification algorithm is holding 0.78 of PRC value, Bayes Net classification algorithm is holding 0.83 of PRC value, and Bagging classification algorithm is holding 0.84 of PRC value.

In FCTH Filter, The SMO classification algorithm is showing the least PRC value which is 0.58 of PRC value. The leading PRC value is produced by Bagging Classifier which is 0.72 of PRC value. The Bayes Net, IBK classifier algorithm, Jrip classification algorithm and Random Forest classifier are having 0.69 of PRC value to 0.71 of PRC value. Such as Bayes Net, IBK and Jrip are holding same PRC value which is 0.69 of PRC value and Random Forest is holding 0.71 of PRC value.

The Edge Histogram of image enhancement technique with selected machine learning classification models are cropping from 0.66 of PRC to 0.89 of PRC value. The FCTH filter with selected machine learning algorithm models are producing 0.58 of PRC value to 0.72 of PRC value. In generally, the Edge Histogram enhancement gives better result compare with FCTH filter technique for borrowed dataset.

The Edge Histogram Filter with Random Forest model yields 0.89 of PRC value which is the highest PRC value compare with other models. The Filter with SMO produces 0.58 of PRC value which is the lowest PRC value compare with other models.

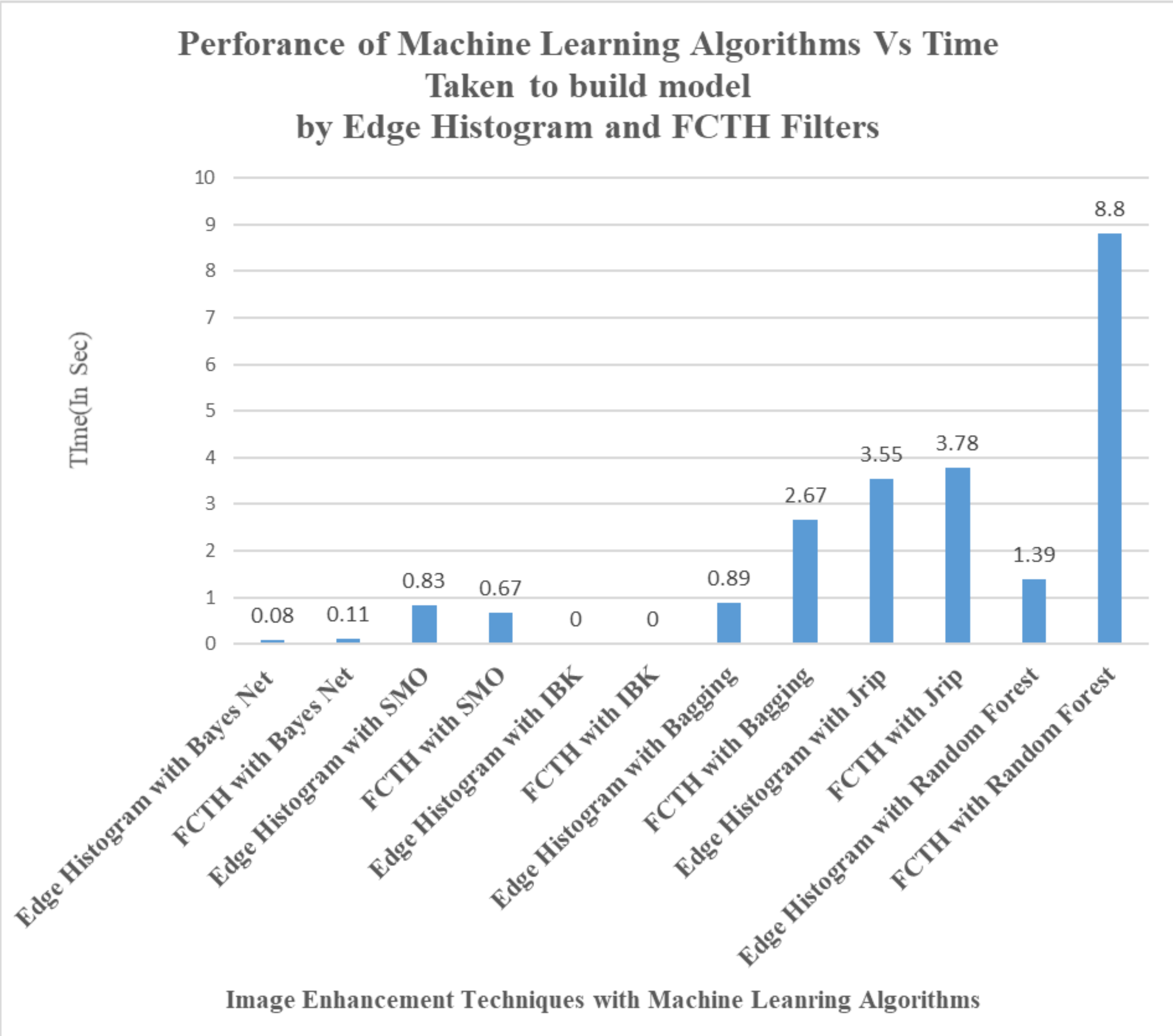

Figure 7: Time Consumption performance of Edge Histogram Filter and FCTH Filter by selected learning approaches

The above diagram 7 shows that the Performance of Time Consumptions to construct models on machine learning algorithms by using Edge Histogram Filter and FCTH Filter.

With the implementation of Edge Histogram, the IBK classification algorithm is taking zero seconds for constructing a model which is least time consumption for building a model. The Jrip classification algorithm is taking huge time for constructing a model which is 3.55 seconds compare with other models. The Bayes Net, SMO, Bagging and Random Forest classification algorithms are taking time consumption for constructing a model from 0.08 seconds to 1.39 seconds. Such as Bays Net is 0.08 seconds, SMO is 0.83, Bagging is 0.89 and Random Forest is 1.39 seconds.

With the implementation of FCTH Filter, the IBK classification algorithm is taking zero seconds for constructing a model which is least time consumption for building a model. The Random Forest classification algorithm is taking maximum time consumption for constructing a model which is 8.80 seconds compare with other models. The Bayes Net, SMO, Bagging and Jrip classification algorithms are taking time consumption for constructing a model from 0.11 seconds to 3.78 seconds. Such as Bays Net is 0.11 seconds, SMO is 0.67 seconds, Bagging is 2.67 seconds and Jrip classifier is 3.78 seconds.

5 Conclusions

This research work finds that the Edge Histogram of image enhancement technique with several machine learning classification models are cropping from 73.36% of accuracy level to 82.85% of accuracy level. The FCTH image enhancement is showing from 64.15% of accuracy level to 67.60% of accuracy level. In generally, Edge Histogram enhancement gives better result compare with FCTH filter technique for borrowed dataset. The Edge Histogram of image enhancement technique with selected machine learning classification models are gaining from 0.73 of precision level to 0.83 of precision level. The FCTH image enhancement technique with selected machine learning algorithms are showing from 0.63 of precision level to 0.79 of precision level. The Edge Histogram of image enhancement technique with selected machine learning algorithms are cropping from 0.73 of hit rate level to 0.83 of hit rate level. The FCTH image enhancement is showing from 0.64 of hit rate level to 0.68 of hit rate level. The Edge Histogram of image enhancement technique with selected machine learning classification models are cropping ROC values between 0.85 of ROC and 0.96 of ROC value. The FCTH image enhancement technique with selected machine learning algorithm is showing from 0.79 of ROC value to 0.86 of ROC value. The Edge Histogram of image enhancement technique with selected machine learning classification models are cropping from 0.66 of PRC to 0.89 of PRC value. The FCTH filter with selected machine learning algorithm models are producing 0.58 of PRC value to 0.72 of PRC value. In generally, the Edge Histogram enhancement gives better result compare with FCTH filter technique for borrowed dataset. The Edge Histogram with Random Forest model shows best result compare with other models. This research work recommends that the Edge Histogram image equalization technique is producing best result compare with FCTH filter technique while applying selected machine learning algorithm. It shows best performances compare with other models for identifying COVID 19 without wasting of investigating unnecessary diagnosing process in health and medical sector.

Conflict of Interest

The authors have no conflicts of interest to declare. The article interpretation and analysis were contributed to by all authors, who also drafted the substantial scientific content.

References

[1] WHO WHO coronavirus (COVID-19) dashboard (2022) https://covid19.who.int/ (Accessed on 5th June 2022)
[2] Chen, W., Yao, M., Zhu, Z. et al. The application research of AI image recognition and processing technology in the early diagnosis of the COVID-19. BMC Med Imaging 22, 29 (2022). https://doi.org/10.1186/s12880-022-00753-1
[3] Yamayoshi S, Sakai-Tagawa Y, Koga M, Akasaka O, Nakachi I, Koh H, Maeda K, Adachi E, Saito M, Nagai H et al. Comparison of rapid antigen tests for COVID-19. Viruses. 2020;12(12).
[4] Shi Y, Wang G, Cai XP, Deng JW, Zheng L, Zhu HH, Zheng M, Yang B, Chen Z. An overview of COVID-19. J Zhejiang Univ Sci B. 2020;21(5):343–60.
[5] Wang W, Tang J, Wei F. Updated understanding of the outbreak of 2019 novel coronavirus (2019-nCoV) in Wuhan, China. J Med Virol. 2020;92(4):441–7.
[6] Habas K, Nganwuchu C, Shahzad F, Gopalan R, Haque M, Rahman S, Majumder AA, Nasim T. Resolution of coronavirus disease 2019 (COVID-19). Expert Rev Anti Infect Ther. 2020;18(12):1201–11.
[7] Riou J, Althaus CL. Pattern of early human-to-human transmission of Wuhan 2019 novel coronavirus (2019-nCoV), December 2019 to January 2020. Euro Surveill. 2020;25(4).
[8] Liu NN, Tan JC, Li J, Li S, Cai Y, Wang H. COVID-19 pandemic: experiences in china and implications for its prevention and treatment worldwide. Curr Cancer Drug Targets. 2020;20(6):410–6.
[9] Liu HC. Artificial intelligence stomatology. Zhonghua Kou Qiang Yi Xue Za Zhi. 2020;55(12):915–9.
[10] Pashkov VM, Harkusha AO, Harkusha YO. Artificial intelligence in medical practice: regulative issues and perspectives. Wiad Lek. 2020;73(12 cz 2):2722–27.
[11] Wagner JB. Artificial intelligence in medical imaging. Radiol Technol. 2019;90(5):489–501.
[12] Wang S, Shi J, Ye Z, Dong D, Yu D, Zhou M, Liu Y, Gevaert O, Wang K, Zhu Y et al. Predicting EGFR mutation status in lung adenocarcinoma on computed tomography image using deep learning. Eur Respir J. 2019;53(3).
[13] Walsh SLF, Calandriello L, Silva M, Sverzellati N. Deep learning for classifying fibrotic lung disease on high-resolution computed tomography: a case-cohort study. Lancet Respir Med. 2018;6(11):837–45.
[14] Walsh SLF, Humphries SM, Wells AU, Brown KK. Imaging research in fibrotic lung disease; applying deep learning to unsolved problems. Lancet Respir Med. 2020;8(11):1144–53.

[15] Abd-Alrazaq A, Alajlani M, Alhuwail D, Schneider J, Al-Kuwari S, Shah Z, Hamdi M, Househ M. Artificial Intelligence in the Fight Against COVID-19: Scoping Review. J Med Internet Res. 2020;22(12):e20756.
[16] Gurmail Singh, Think positive: An interpretable neural network for image recognition, Neural Networks, Volume 151, 2022, Pages 178-189, ISSN 0893-6080, https://doi.org/10.1016/j.neunet.2022.03.034.
[17] H. Mary Shyni, E. Chitra, A COMPARATIVE STUDY OF X-RAY AND CT IMAGES IN COVID-19 DETECTION USING IMAGE PROCESSING AND DEEP LEARNING TECHNIQUES, Computer Methods and Programs in Biomedicine Update, Volume 2, 2022, 100054, ISSN 2666-9900, https://doi.org/10.1016/j.cmpbup.2022.100054.
[18] Haghanifar, A., Majdabadi, M.M., Choi, Y. et al. COVID-CXNet: Detecting COVID-19 in frontal chest X-ray images using deep learning. Multimed Tools Appl (2022). https://doi.org/10.1007/s11042-022-12156-z
[19] Lin Yang, Shui-Hua Wang ,and Yu-Dong Zhang, EDNC: Ensemble Deep Neural Network for COVID-19 Recognition, Tomography 2022, 8(2), 869-890; https://doi.org/10.3390/tomography8020071
[20] Meng Li et.al. Machine Vision and Intelligent Algorithm Based on Neural Network,Computational Intelligence and Neuroscience, Volume 2022, https://doi.org/10.1155/2022/6154453
[21] Priya Aggarwal, Narendra Kumar Mishra, Binish Fatimah, Pushpendra Singh, Anubha Gupta, Shiv Dutt Joshi,COVID-19 image classification using deep learning: Advances, challenges and opportunities,Computers in Biology and Medicine,Volume 144,2022,105350,ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2022.105350.
[22] Rabab Ali Abumalloh, Mehrbakhsh Nilashi, Muhammed Yousoof Ismail, Ashwaq Alhargan, Abdullah Alghamdi, Ahmed Omar Alzahrani, Linah Saraireh, Reem Osman, Shahla Asadi, Medical image processing and COVID-19: A literature review and bibliometric analysis, Journal of Infection and Public Health, Volume 15, Issue 1, 2022, Pages 75-93, ISSN 1876-0341, https://doi.org/10.1016/j.jiph.2021.11.013.
[23] Rajawat, N., Hada, B.S., Meghawat, M. et al. C-COVIDNet: A CNN Model for COVID-19 Detection Using Image Processing. Arab J Sci Eng (2022). https://doi.org/10.1007/s13369-022-06841-2
[24] S. V. Kogilavani , J. Prabhu, R. Sandhiya, M. Sandeep Kumar, UmaShankar Subramaniam,Alagar Karthick , M. Muhibbullah , and Sharmila Banu Sheik Imam, COVID-19 Detection Based on Lung Ct Scan Using Deep Learning Techniques, Social Network-Based Medical Informatics with a Deep Learning Perspective, Volume 2022 ,Article ID 7672196, https://doi.org/10.1155/2022/7672196
[25] Sun, Junding et al. “TSRNet: Diagnosis of COVID-19 based on self-supervised learning and hybrid ensemble model.” Computers in biology and medicine, vol. 146 105531. 16 Apr. 2022, doi:10.1016/j.compbiomed.2022.105531
[26] Ter-Sarkisov, A. COVID-CT-Mask-Net: prediction of COVID-19 from CT scans using regional features. Appl Intell (2022). https://doi.org/10.1007/s10489-021-02731-6
[27] B. Arulanandam, H. Beladi, A. Chakrabarti,”COVID-19 mortality and the overweight: cross-country evidence”,J Public Health Manag Pract (2021), Article 100179.
[28] B. Pandey, D.K. Pandey, B.P. Mishra, W. Rhmann, A comprehensive survey of deep learning in the field of medical imaging and medical natural language processing: challenges and research directions,J King Saud Univ Comput Inf Sci (2021), 10.1016/j.jksuci.2021.01.007
[29] D. Müller, I.S. Rey, F. Kramer, Robust chest CT image segmentation of COVID-19 lung infection based on limited data, IEEE Access, 25 (2021), pp. 1-11.
[30] D.I. Morís, J.J. de Moura Ramos, J.N. Buján, M.O. Hortas,Data augmentation approaches using cycle-consistent adversarial networks for improving COVID-19 screening in portable chest X-ray images, Expert Syst Appl, 185 (2021), Article 115681
[31] D.L. Fung, Q. Liu, J. Zammit, C.K.-S. Leung, P. Hu, Self-supervised deep learning model for COVID-19 lung CT image segmentation highlighting putative causal relationship among age, underlying disease and COVID-19, J Transl Med, 19 (1) (2021), pp. 1-18
[32] D. Singh, V. Kumar, V. Yadav, M. Kaur,Deep neural network-based screening model for COVID-19-Infected patients using chest X-ray images, International Journal of Pattern Recognition and Artificial Intelligence, Vol. 35, No. 03, 2151004 (2021).https://doi.org/10.1142/S0218001421510046
[33] F. Xie, Z. Huang, Z. Shi, T. Wang, G. Song, B. Wang, et al., DUDA-Net: a double U-shaped dilated attention network for automatic infection area segmentation in COVID-19 lung CT images, Int J Comput Assist Radiol Surg (2021), pp. 1-10.
[34] https://www.kaggle.com/c/rsna-pneumonia-detection-challenge/data
[35] https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia
[36] WEKA: http://www.cs.waikato.ac.nz.
[37] S. M. Manimegalai et al., Image Classifications On Covid 19 CXR Images Using Auto Color Correlogram Filter , Indian Journal of Computer Science and Engineering (IJCSE), e-ISSN : 0976-5166 p-ISSN : 2231-3850, Vol. 12 No. 5 Sep-Oct 2021,pp- 1288-1301.
[38] Vijayan T, Sangeetha M, A. Kumaravel, Karthik B, “Feature selection for Simple Color Histogram Filter based on Retinal Fundus Images for Diabetic Retinopathy recognition,” IETE Journal of Research, 2020. https://doi.org/10.1080/03772063.2020.1844082.
[39] Vijayan T, Sangeetha M, Karthik B, “Efficient Analysis of Diabetic Retinopathy on Retinal Fundus Images using Deep Learning Techniques with Inception V3 Architecture,” Journal of Green Engineering, Vol 10, Issue 10, pp. 9615-9625. Oct 2020.

Authors Profile

Mrs. S.M.Manimegalai, Ph. D Research scholar, Vivekanandha College of Arts and Science for Women (A), Elayampalayam-637205, Tiruchengode. Having 14 Years of teaching experience in DRBCCC Hindu College at Pattabiram-72. My area of interest is Image Processing and Machine Learning, and AI. Participated 20 FDP programmes and 15 seminars and workshops. I have published and presented 5 Research article in International conference. I received 2 times best paper award in International Conference, at Hindustan College of Arts and Science at Kelambakkam, chennai-603103.

Dr. T. Ramaprabha, I have been working as Professor in Department of Information Technology, PG and Research Department of Computer Science and Computer Application, Vivekanandha College of Arts and Science for Women (A), Elayampalayam- 637205. I am having 24 years of teaching and 18 years of research experience. I published more than 42 research articles in international journals and conferences. I completed 9 funded projects and committed with various academic bodies. Now, I am guiding 6 Ph.D. scholars. My area of interest is Image processing, Data mining, Machine learning and Networking.