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Performance Analysis using SCH Filter on Alzheimer's Disease using Machine Learning Algorithm

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Abstract: Alzheimer's disease (AD) is a progressive neurodegenerative disorder, accounting for nearly 60% of all dementia cases. The occurrence of the disease has been increasing rapidly in recent years. Presently about 46.8 million individuals suffer from AD worldwide. The current absence of effective treatment to reverse or stop AD progression highlights the importance of disease prevention and early diagnosis. This research work finds that image feature extraction such as simple RGB Histogram Filter techniques on Alzheimer's images dataset by implementing statistical learning. The Decision tree – J48 Classifier optimizer of ensemble category produced 51% of accuracy level, 0.510 of True Positive (TP) rate value, 0.163 of False Positive (FP) rate value, 0.507 of precision value, 0.510 value of recall value, 0.718 of receiver operating character (ROC) value and 0.478 of precision recall curve (PRC) value and it takes time consumption as 0.03 seconds to build a model which is produced as optimal results based on their performance compare with other models. The trees classifier of the J48 is best model for my proposed system.

Keywords: Simple Histogram Filter, Decision Tree, Alzheimer's disease, Random forest, J48**.**

1. INTRODUCTION

The recognition of Alzheimer's disease using machine-learning approaches has several outcomes, but needs a collection of high accuracy, short processing time, and generalizability to various populations for successful application in clinical settings [1, 2]. The detection of Alzheimer's cannot find in the first stages within the current scenario. Earlier detection of this disease can help in providing the specified treatment to stop it happening anytime sooner as there is no cure for this disease. Alzheimer's malady is a highly acknowledged kind of dementia. It is a progressive disease beginning with mild memory loss and possibly leading to loss of the ability to carry on a conversation and respond to the environment. Alzheimer's disease is a brain disorder that slowly destroys memory and thinking skills and, eventually, the ability to carry out the simplest tasks. People with Alzheimer's also experience changes in behavior and personality. Alzheimer's disease is the mostly affects the people who are crossing 65 years old and is categorized by continue deterioration of cognitive and memory abilities [3, 4].

The Image collections and processing of neuroimaging collected from magnetic resonance imaging, functional MRI, positron emission tomography, and diffusion tensor imaging, conducted by expert persons. An early detection of Alzheimer's disease and its prodromal stage, moderate cognitive impairment, is critical. A valid diagnosis based on brain imaging is required, and a strong diagnostic system assisted by neuroimaging processing can permit for a more useful and reliable approach, and potentially enlarged diagnostic accuracy. Traditional methods for examining neuroimaging biomarkers for the testing and analysis of neuropsychiatric diseases relied on mass univariate statistics approach, presumptuous that various brain areas function separately. However, given our present understanding of brain function, this assumption is incorrect [5].

The organization of proposed research work as follows: Section 2 shows the literature review; section 3 displays the materials and methods techniques; section 4 provides the proposed system; section 5 provides the experimental results and lastly, section 5 shows the conclusion.

2. LITERATURE REVIEW

Early successes in medical image processing gained in 2D pictures like Chest X-Ray (CXR) and retinal images [6], which later expanded to 3D images like magnetic resonance imaging. Existing Convolution Neural Networks-based magnetic resonance imaging processes are usually categorized on Level 2. During preprocessing, various works [7, 8] segment the grey matter area and subsequently use it as a Convolutional Neural Networks input.

Three Dimensional with Convolutional Neural Networks has dropout, batch normalization, as well residual module regularization techniques [9]. Multimodal DL techniques have sought to enhance the classification accuracy of AD by using multiple inputs and DL models. For Alzheimer's disease diagnosis utilizing brain Magnetic Resonance Imaging (MRI) data processing, Islam and Zhang [10-12] developed an ensemble of three deep Convolutional Neural Networks (CNN) with slightly varying topologies.

3. MATERIALS AND METHODS

In this segment concentrations on the Materials and methods on this research work. Alzheimer's dataset borrowed from Kaggle repository. The below table shows that the description of the borrowed dataset

Table 1: Alzheimer's Data Set

S.No	Category	Actual Image Size	Processed Image Size	Sample Size
1	Non Demented	256 x 256	176 x 208	50
2	Very Mild Demented	256 x 256	176 x 208	50
3	Mild Demented	256 x 256	176 x 208	50
4	Moderate Demented	256 x 256	176 x 208	50
			Total Instance	**200**

3.1. Methods

The succeeding methods applied in this research work.

1) Borrowed dataset
2) Data preprocessing
3) Apply simple RGB Histogram – Simple Color Histogram-Filter
4) Apply for Trees and Functions in machine learning algorithms

a) Trees: Random Forest, Logistic Model Tree (LMT) and J48 in Decision Tree.
b) Functions: Logistic, Simple Logistic and Sequential Minimal Optimization (SMO).

5) To get an Optimization results
6) Find a best Model

4. PROPOSED SYSTEM

4.1. Time taken to build a model: The Functions classifier of the Logistic category takes 0.1 seconds to build a model , the Functions classifier of the simple logistic category takes 0.2 seconds to build a model, the functions Classifier of the SMO Category takes 0.12 seconds to build a model, the Trees classifier of the LMT category takes 1.03 seconds to build a model, the Trees classifier of the Random Forest category takes 019 seconds to build a model and Trees classifier of the J48 category takes 0.03 seconds to build a model. The trees classifier of the J48 is best model for my proposed system

4.2. Accuracy Value : The Function classifier of the Logistic category produced as a 49% of accuracy value, the Functions classifier of the simple logistic category generated 43.5 % value, the functions Classifier of the SMO Category generated as a 46.2 % value, the trees classifier of the LMT category generates 41% value, the trees classifier of the Random Forest category generated 50.5 % value and Trees classifier of the J48 category generated 51 % value of highest accuracy

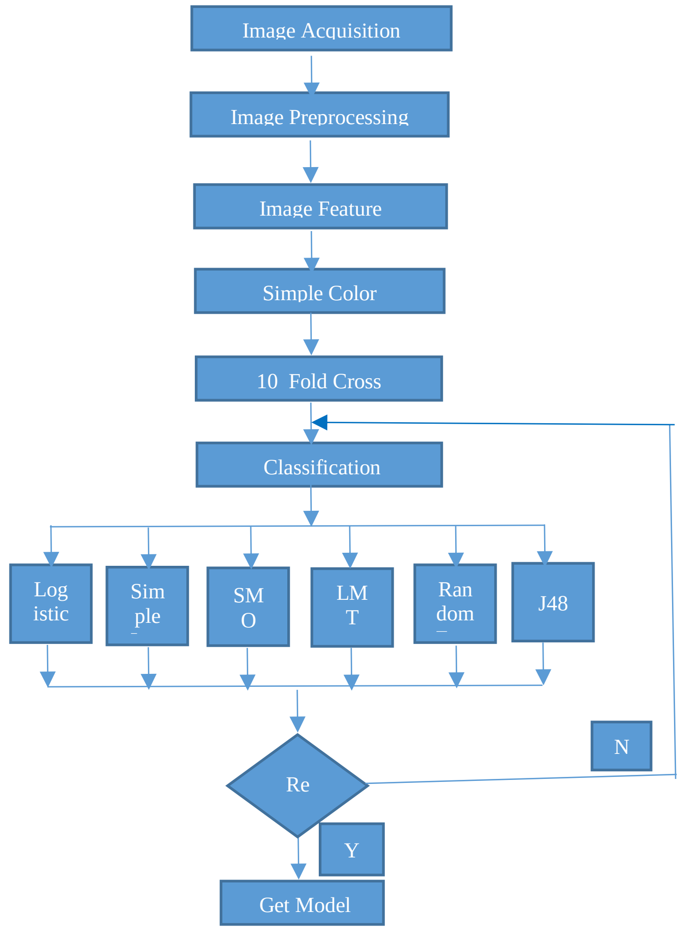

Figure 1: The proposed system

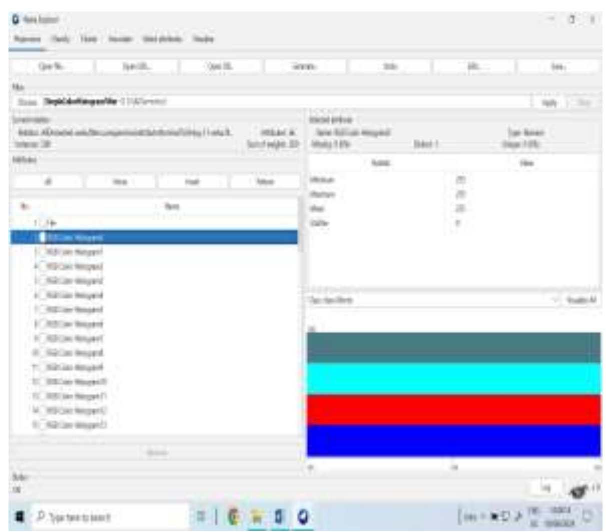

Figure 2: Class Distribution in Weka

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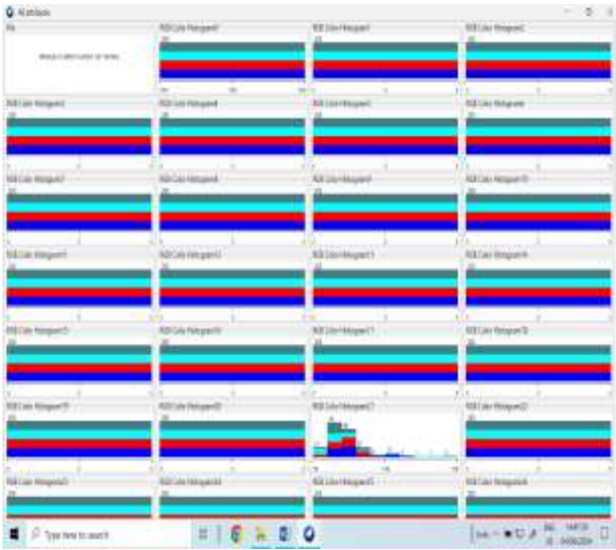

Figure 3: Alzheimer's Image Enhancement of Simple Color Histogram (SCH) filter technique

Table 2: Performance of Trees and Functions Classifier

S.No	Classifier	Base category	Time Taken to build model	Accuracy	TP Rate	FP Rate	Precision	Recall	ROC	PRC
1	Functions	Logistic	0.1	49 %	0.490	0.170	0.473	0.490	0.736	0.488
2	Functions	Simple Logistic	0.2	43.5%	0.435	0.188	0.392	0.435	0.689	0.430
3	Functions	SMO	0.12	46.5%	0.465	0.178	0.450	0.465	0.690	0.391
4	Trees	LMT	1.03	41%	0.410	0.197	0.356	0.410	0.689	0.421
5	Trees	Random Forest	0.19	50.5%	0.505	0.165	0.474	0.505	0.708	0.561
6	Trees	J48	0.03	51%	0.510	0.163	0.507	0.510	0.718	0.478

4.3. True Positive (TP) Rate Value: The Functions classifier of the Logistic category produced as a 0.490 of TP Rate value, the Functions classifier of the simple logistic category generates 0.435 of TP Rate value , the functions Classifier of the SMO Category generates 0.465 of TP Rate value , the Trees classifier of the LMT category generates 0.410 of TP Rate value, the Trees classifier of the Random Forest category generates 0.505 of TP Rate value and Trees classifier of the J48 category generates highest value of 0.510 for TP Rate value

4.4. False Positive (FP) Rate Value: The Functions classifier of the Logistic category produced as a 0.170 of FP Rate value, the Functions classifier of the simple logistic category generates 0.188 of FP Rate value , the functions Classifier of the SMO Category generates 0.178 of FP Rate value, the Trees classifier of the LMT category generates 0.197 of FP Rate value , the Trees classifier of the Random Forest category generates 0.165 of FP Rate value and Trees classifier of the J48 category generates lowest value of 0.163 for FP Rate value.

4.5. Precision Value: The Functions classifier of the Logistic category produced as a 0.473 of precision value , the Functions classifier of the simple logistic category generates 0.392 of precision value, the functions Classifier of the SMO Category generates 0.450 of precision value, the Trees classifier of the LMT category generates 0.356 of precision value, the Trees classifier of the Random Forest category generates 0.474 of precision value and Trees classifier of the J48 category generates highest value 0.507 of precision value.

4.6. Recall Value: Functions classifier of the Logistic category produced as a 0.490 of recall value, the Functions classifier of the simple logistic category generates 0.435 of recall value, the functions Classifier of the SMO Category generates 0.465 of recall value, the Trees classifier of the LMT category generates 0.410 of recall value, the Trees classifier of the Random Forest category generates 0.505 of recall value and Trees classifier of the J48 category generates highest recall value whose value is 0.510.

4.7. Receiver Operating Character (ROC) value : the Functions classifier of the Logistic category produced as a 0.736 of ROC value, the Functions classifier of the simple logistic category generates 0.689 of ROC value, the functions Classifier of the SMO Category generates 0.690 of ROC value, the Trees classifier of the LMT category generates 0.689 of ROC value, the Trees classifier of the Random Forest category generates 0.708 of ROC value and Trees classifier of the J48 category generates highest ROC value whose value is 0.718

4.8. Precision Recall Curve (PRC) value : the Functions classifier of the Logistic category produced as a 0.488 of PRC value, the Functions classifier of the simple logistic category generates 0.430 of PRC value, the functions Classifier of the SMO Category generates 0.391 of PRC value, the Trees classifier of the LMT category generates 0.421of PRC value, the Trees classifier of the Random Forest category generates highest value of PRC which is 0.561 and Trees classifier of the J48 category generates second highest PRC value whose value is 0.478.

5. EXPERIMENTAL RESULTS OF CLASSIFIER Vs BASE CATEGORY

Figure 4. Performance of various classifier with Time taken to build a model

The above Figure 4 depicts the classifiers' time taken to build a model performances after being chosen that the longest time taken to build model value of 1.03 seconds which is produced by LMT classifier and other classifier such as simple Logistic, SMO, Logistic, and Random forest classifier. The J48 classifier produced minimum time taken to build model is 0.03 seconds.

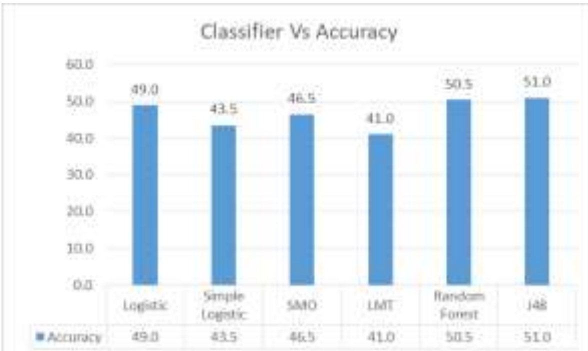

Figure 5. Performance of various classifier with Accuracy

The above Figure 5 shows that the highest accuracy of 51.0 value, which is produced by J48 classifier. The LMT and SMO, Simple Logistic and Logistic are having accuracy from 40 to 49 value. The Random Forest classifier produced second highest accuracy of 50.5 value.

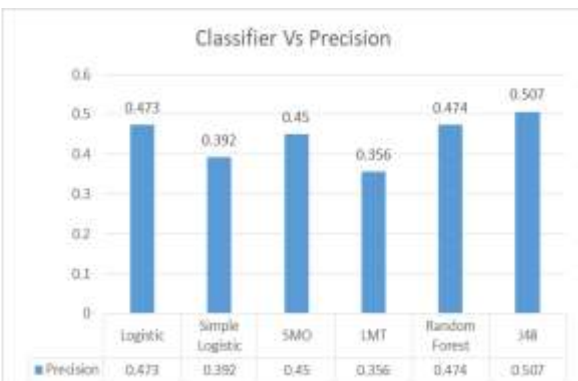

Figure 6. Performance of various classifier with Precision value

The above Figure 6 shows that the highest precision value is 0.507, which produced by J48 classifier. The LMT, SMO, Simple Logistic, Random Forest and Logistic are having precision value from 0.3 to 0.4 value.

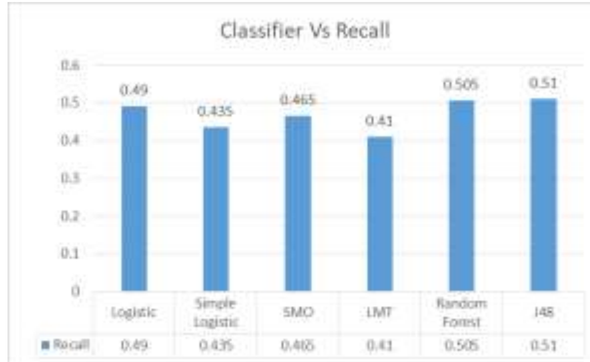

Figure 7. Performance of various classifier with Recall value

The above Figure 7 shows that the highest recall value which produced by J48 classifier. The LMT, SMO, Simple Logistic, Random Forest and Logistic produced recall value from 0.410 to 0.5.5 value.

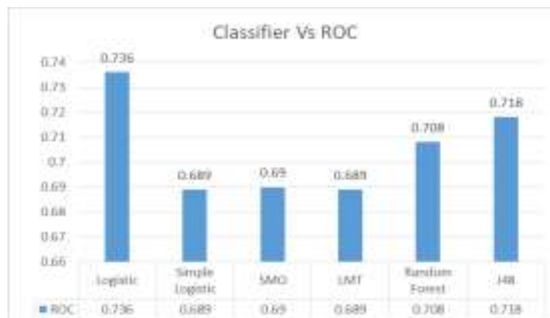

Figure 8. Performance of various classifier with ROC value

The above Figure 8 shows that the highest ROC value which produced by Logistic classifier. The LMT, SMO, Simple Logistic, Random Forest and Logistic classifier produced recall value from 0.689 to 0. 708 value. The second highest ROC value 0.718 produced by J48 classifier.

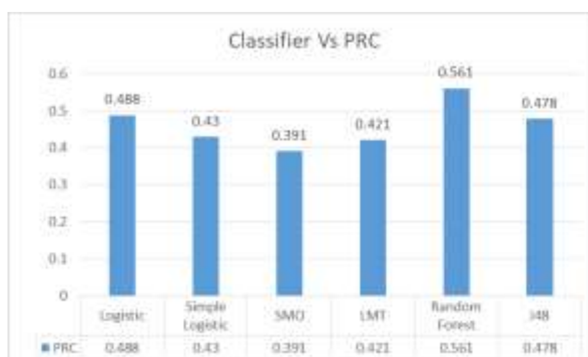

Figure 9. Performance of various classifier with PRC value

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The above Figure 8 shows that the highest PRC value 0.561 which produced by Random Forest classifier. The LMT, SMO, Simple Logistic, J48 and Logistic classifier produced PRC value from 0.391 to 0.488 value.

Figure 10. Performance of various classifier with TP Rate

The above Figure 10 shows that the highest TP rate which produced by J48 classifier. The LMT, SMO, Simple Logistic, Random Forest and Logistic classifier produced TP rate from 0.490 to 0.505 value.

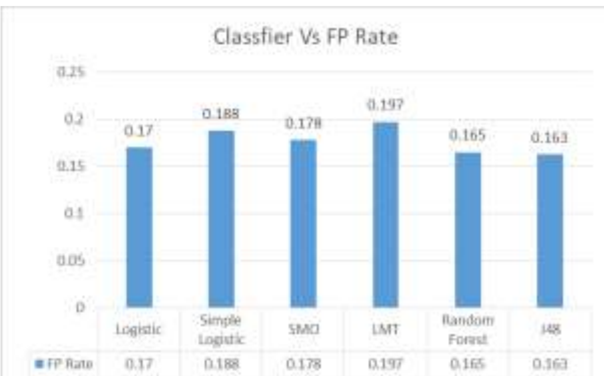

Figure 11. Performance of various classifier with FP Rate

The above Figure 11 shows that the lowest FP rate value 0.163 which produced by J48 classifier. The LMT, SMO, Simple Logistic, Random Forest and Logistic classifier produced FP rate value from 0.165 to 0.197 value.

6. CONCLUSION

This research work finds that the Decision tree – J48 Classifier optimizer of ensemble category produced 51% of highest accuracy level, 0.510 of highest True Positive (TP) rate value, 0.163 of lowest False Positive (FP) rate value, 0.507 of highest precision value, 0.510 of highest recall value, 0.718 of receiver operating character (ROC) value and 0.478 of precision recall curve (PRC) value and decision tree – J48 Classifier takes minimum time consumption of 0.03 seconds to build a model which is produced as optimal results based on their performance compare with other models. The J48 Classifier is the best model to train the Alzheimer's disease among other classifiers.

7. REFERENCES

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