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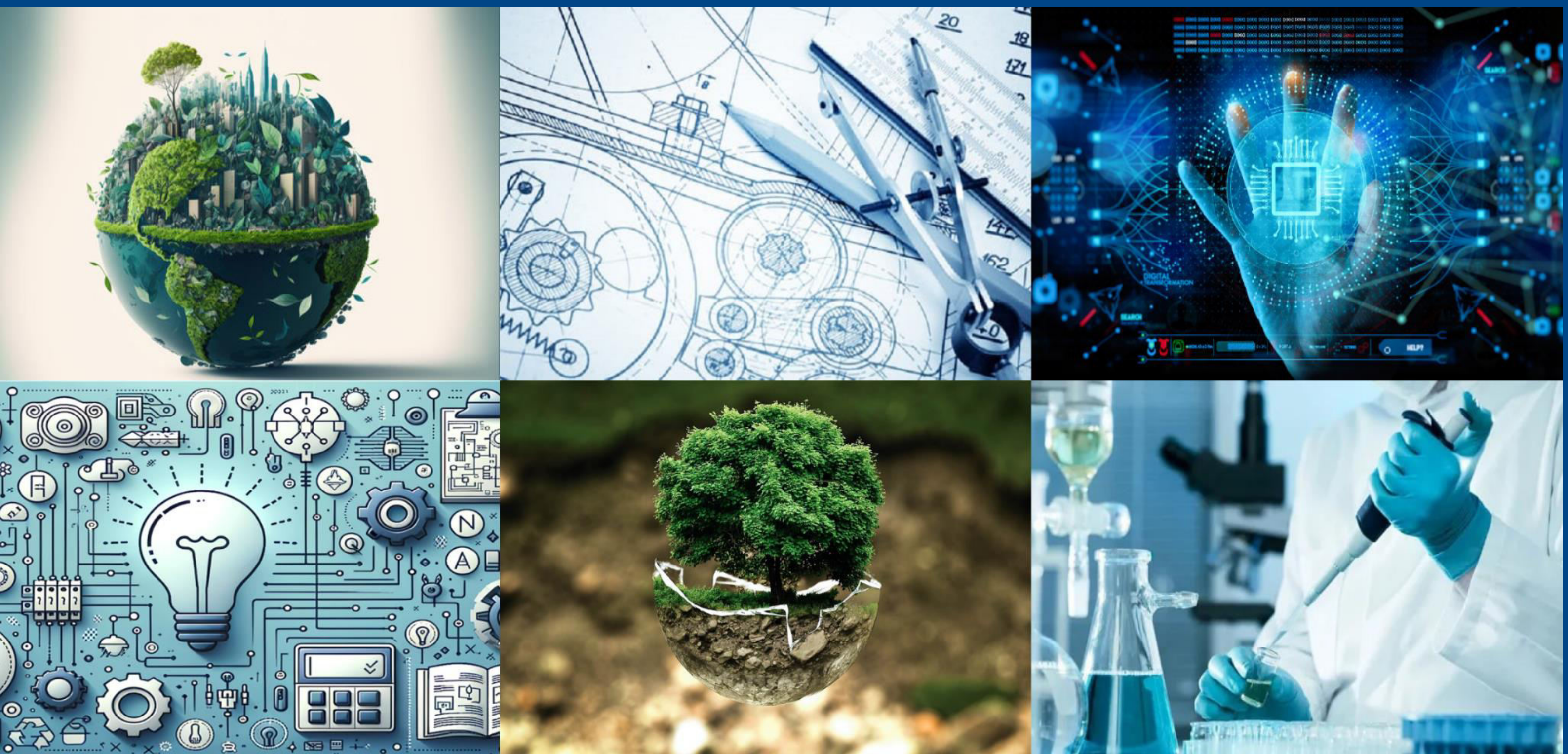

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Fuzzy Color and Texture Histogram Filter-Based Feature Extraction with Machine Learning Classifiers for Automated Alzheimer's Disease Classification from MRI Images

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ABSTRACT: Alzheimer's disease (AD) is the most prevalent Neurodegenerative disorder in the world, which leads to permanent destruction of the neurons and gradual deterioration of cognition. Defining the severity stages of AD as early and accurately as possible, using neuroimaging data, is critical for the effective provision of timely clinical intervention, disease monitoring and therapeutic decision making. MRI (magnetic resonance imaging) is the most accurate neuroimaging technique to diagnose Alzheimer's, and the high-resolution, structural brain images can be correlated with disease symptoms, such as atrophy (loss of brain structure) and a decrease in the size of a brain structure called the hippocampus. In this work, the objective is to investigate the efficiency of Fuzzy Color and Texture Histogram (FCTH) Filter as a technique for extracting the features of MR images for the automatic classification of Alzheimer's disease using six machine learning classifiers namely; Logistic Regression, Ridge Classifier, Gaussian Naive Bayes, Multinomial Naive Bayes, k-Nearest Neighbors, and Radius Neighbors. From Kaggle (https://www.kaggle.com/datasets/azminur2856/alzheimer-mri-dataset), Alzheimer's MRI Dataset was used to evaluate. All MRI images were processed to obtain FCTH and finally were assessed independently by six classifiers of machine learning framework Weka 3.8. The accuracy, precision, recall, ROC area, PRC area and training time were used to assess performance. FCTH Filter + Multi Naive Bayes had the highest accuracy of 85.11%, the highest ROC area of 0.90 and highest PRC area of 0.88 and took 3.21 seconds to train. The best training time was obtained by FCTH Filter + k-Nearest Neighbors with the accuracy of 84.21%. The accuracy of FCTH Filter + Logistic Regression was at 78.17% while the training time was at 15.12 seconds. The overall performance of the classifiers in the classification of the Alzheimer's MRI is best with FCTH+Multinomial Naive Bayes and the most efficient in computation with k-Nearest Neighbours. The FCTH-based pipeline is an interpretable and computationally simple automatic classification system for Alzheimer's MRI, which can be easily applied to clinical practice.

KEYWORDS: Alzheimer's Disease, memory loss, behavioral changes, neurological symptoms, MRI.

I. INTRODUCTION

Alzheimer's disease (AD) is the most common type of dementia, accounting for 60-70% of all dementia cases, and currently (2023) it is estimated that 55 million people have Alzheimer's disease worldwide, increasing to nearly 300 million by 2050 [1]. Episodic memory loss, language dysfunction, executive dysfunction and eventual loss of independent functioning in daily life are key features of AD which are progressive, irreversible and neurodegenerative. The different patterns of cortical atrophy, loss of hippocampal volume and enlargement of the ventricles along the

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disease continuum, from preclinical stages to mild cognitive impairment and mild, moderate and severe dementia, have been identified on structural MRI [2].

Early and accurate recognition of the severity of Alzheimer's disease is clinically important for the following reasons: 1) Pharmacological and non-pharmacological treatment that can slow the progression of Alzheimer's disease can be initiated early; 2) This early and accurate diagnosis can guide the therapeutic decision making and planning for the treatment of Alzheimer's disease; and 3) The early and accurate diagnosis can prepare patients and families for the expected trajectory of cognitive decline [3]. The diagnosis of Alzheimer's disease is clinically important, but is challenging in practice, requiring a team of neuropsychologists, biomarker analysis and clinical judgment from the interpretation of expert neuroimages, which is time consuming, resource intensive and prone to interrater variability [4].

The most widely recognized imaging modality of the brain that is used in the assessment of Alzheimer's is Magnetic Resonance Imaging (MRI) which yields high-resolution structural images of the brain, reflecting the regional atrophy patterns associated with the progression of Alzheimer's. A promising direction towards standardised, scalable and rapid disease staging in situations where specialised neuroimaging expertise is not available is the use of automated machine learning (ML) techniques for classifying magnetic resonance imaging (MRI) scans of Alzheimer's (AD) patients [5]. The quality of the descriptor directly affects the classification performance and image feature extraction is a crucial intermediate processing step between the raw MRI pixel data and the input to image classifiers.

Fuzzy Color and Texture Histogram (FCTH) Filter is an image descriptor, which is composed of fuzzy colour quantization and co-occurrence texture encoding which provides a compact feature vector that represents the distribution of colour and structural texture patterns in medical images [6]. Spatial distribution of signal intensity and local texture changes were quantified by brain MRI, and were correlated with morphological changes of the brain, such as hippocampal shrinkage, sulcal widening, and cortical thinning, related to Alzheimer's disease progression.FCTH measured the spatial patterns of the signal intensity and local texture changes that were related to the spatial changes in the brain volumes connected to the evolution of Alzheimer's disease, as seen in brain MRI, such as cortical thinning, widening of sulci and hippocampal shrinkage. For the present study, six machine learning classifiers were employed to compare the features extracted from the FCTH, with the intent of finding the optimal combination of features extracted from the FCTH and the machine learning classifiers for automated AD classification on the Alzheimer's MRI Dataset from Kaggle.
Paper is organized as follows. Section II describes related works, materials and methods are given in Section III. Section IV presents experimental results showing results of images tested. Finally, Section V presents conclusion.

II. RELATED WORK

The neuropathological basis of Alzheimer's disease has been established by decades of research, both post mortem and in vivo, neuroimaging. Presence of amyloid beta plaques and neurofibrillary tangles lead to a cascade of synaptic dysfunction and neuronal death resulting in progressive cortical and subcortical atrophy seen on MRI [1]. In the earliest and earliest preclinical stages of AD, initial MRI studies revealed a volume measurement of hippocampus is one of the earliest and most sensitive measures of AD [2]. They are successively affected, leading to a typical regional atrophy pattern which can be semi-quantitatively analyzed by automated morphometry and texture analysis [3].

A clinical staging framework for AD has been established and includes the Alzheimer Disease Clinical Rating scale (CDR) and the National Institute on Aging/Alzheimer's Association (NIA-AA) criteria which classify the disease as non-demented, very mildly demented, mildly demented, and moderately demented. The stages are connected to successive structural MRI changes that constitute the basis of automated classification methods [4]. Further the importance of the clinical need of sensitive automated classification systems in the early stages of pre-dementia and mild dementia has been demonstrated to have the greatest therapeutic value [5] again underscoring the clinical urgency of the topic.

A variety of approaches have been used with machine learning to classify Alzheimer's disease using MRI images. Volumetric morphometry, voxel-based morphometry (VVM), cortical thickness measurements and texture features in addition to support vector machines, random forests, and naive Bayes (NB) classifiers have been used for AD staging tasks [6]. The advantages of these methods over deep learning are the interpretability, especially the ability to directly map the importance of features to clinically relevant biomarkers derived from neuroimaging data, which can be checked against neuropathological knowledge.

One of these classical machine learning methods is the Naive Bayes classifiers and it is robust and scalable to high dimensional medical image feature spaces without being affected by the curse of dimensionality [7]. The Multinomial Naive Bayes variant of the classifiers was one of the most successful classifiers in this study and have already been applied to various neuroimaging classification problems [8] where the local neighbourhood structure in the high dimensional space of the MRI texture features is a meaningful proximity measure for assigning the class of the AD stage.

The accuracy of automated detection of Alzheimer's is greatly enhanced by deep convolutional neural networks when analyzing MRI images. Different tasks of AD staging have been performed with high level of accuracy (close to clinical level) using end-to-end deep learning models applied to large annotated MRI datasets [9]. Transfer learning techniques have been successfully applied to classification of Alzheimer's MRI images with 100% accuracy using pre-trained CNN architectures, such as VGG, ResNet and InceptionV3, which are trained on large data sets of natural images and then fine-tuned on neuroimaging data sets [10].

The deep learning approaches have a number of limitations when applied on a clinical level to the diagnosis of Alzheimer's disease, however: They require large, carefully annotated training sets of MRI images; They require GPUs that are not common in clinical environments; They produce black-box feature representations that are hard to interpret in a clinical sense and this is crucial in the context of regulatory validation and clinical trust in the field of neurology. The handcrafted feature descriptors along with interpretable classifiers provide a clinically transparent option in terms of the classifiers, and it does not compromise on its accuracy either, which has complete explainability and computational efficiency.

Texture features have a proven place in classification study of Alzheimer's using MRI images. Second order statistics of the intensities of pixels have been used to quantify the textural differences in white matter and gray matter structures from healthy controls to individuals with AD, using the Gray-Level Co-occurrence Matrix (GLCM). [12] The microstructural changes of the brain associated with neurodegeneration, such as demyelination, axonal loss, and gliosis are linked to these texture changes.

Fuzzy Color and Texture Histogram (FCTH) descriptor is an enhanced version of classical colour and texture histogram based descriptor proposed for texture description using fuzzy logic membership functions for colour bin assignment which reduces the quantization effect and hence improves the texture description when there are different MRI acquisition parameters [13]. Combining the global signal intensity profile of the MRI slices (representing tissue density and atrophy) and the local textural profile of the specific brain regions associated with Alzheimer's neurodegeneration, FCTH is able to encode both the color (signals) and texture (structural pattern) information in a single compact descriptor. Previous research has confirmed the effectiveness of FCTH for medical image retrieval and classification problems, such as skin disease [14] and general medical image classification applications [15] and in the present study, the effectiveness of FCTH was tested for Alzheimer's MRI classification.

The systematic combination evaluation of feature-classifiers based on their performances has been recognized as the standard methodological paradigm, for benchmarking medical image classification problems. Comparisons of classifiers in feature extraction methods and of different families of classifiers show that the influence of the quality of the features is predominant, and the choice of the classifiers is modulating [6]. For the neuroimaging applications, probabilistic classifiers with texture-based feature descriptors like Naive Bayes classifiers are shown to be competitive with respect to the accuracy of Alzheimer's staging tasks on benchmark datasets and to offer complete interpretability and computational efficiency for deployment into clinical settings [7,8]. The Weka machine learning system can provide a standardized and repeatable environment to these comparisons, allowing evaluation of classification pipeline to be reported and reproduced transparently [15].

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III. METHODOLOGY

3.1 Dataset

We got the Alzheimer's MRI Dataset from Kaggle (https://www.kaggle.com/datasets/azminur2856/alzheimer-mri-dataset). The data set contains the MRI scans of a patient's brain measured at five different levels of severity, corresponding to five stages of Alzheimer's disease: Non-Demented, Very Mildly Demented, Mildly Demented, Moderately Demented, and Without Dementia. The dataset allows to directly compare the performance of the feature extraction and the classifiers in standard experimental conditions. In all experiments, the Weka 3.8 machine learning workbench [15] was implemented and used for running the experiments.

3.2 Image Preprocessing

All MRI images were pre-processed using a standard pre-processing pipeline prior to extracting FCTH features. The images were all resized to a fixed spatial resolution (224 × 224) to ensure that the features were extracted at the same scale. The MRI signal intensity differences between MRI acquisition protocols were normalized to [0, 1] to correct for the scanner-dependent signal intensity. To ensure an unbiased evaluation, no data augmentation was carried out, while keeping the original neuroimaging data distribution intact [9].

3.3 Fuzzy Color and Texture Histogram (FCTH) Feature Extraction is based on fuzzy logic

The Fuzzy Color and Texture Histogram is a small image descriptor, which combines the quantization of colors based on fuzzy logic with the co-occurrence of texture. [13] The extraction procedure of FCTH is as follows: (i) Dividing the MRI image into non-overlapping spatial blocks; (ii) calculating the fuzzy membership functions that assigns the intensity value of each pixel to multiple color/intensity bins with soft boundaries avoiding hard quantization artifacts of conventional histograms; (iii) computing texture features based on spatial co-occurrence statistics of the intensity transitions in each spatial block; (iv) the fuzzy color histogram and texture histogram are concatenated to form the complete FCTH feature vector.

In Alzheimer's MRI classification, FCTH is encoded with: (i) global intensity distribution shifts that model general intensity distribution changes in the gray matter and white matter that accompany the atrophy process; (ii) local texture irregularities in FCTH blocks that model changes in the local texture of the hippocampus and entorhinal cortex regions known to be early indicators of AD; and (iii) sulcal widening and ventricular enlargement signatures derived from the spatial intensity distribution of FCTH blocks. The fuzzy membership approach is especially beneficial for MRI data because there is variability in intensity distribution between scanners and sessions due to the nature of the intensity distribution that does not adhere to hard bin boundaries [13,14].

3.4 Machine Learning Classifiers

The feature vectors obtained using the FCTH were independently tested for six classifiers:

Logistic Regression: Probabilistic linear classifiers using the softmax function of a linear combination of the FCTH features and to estimate posterior probabilities of the Alzheimer's class. Regularization is used in order to avoid overfitting, since the FCTH feature space is high dimensional.

Ridge Classifier: Regularized linear classifier, using L2 penalty on feature coefficients of FCTH, which is less sensitive to the multicollinearity of the correlated color-texture histogram bins and more stable to generalization.

3. Gaussian Naive Bayes: Probabilistic Classifier Model with Gaussian Conditional Distribution for each feature dimension (FCTH) of training data for a particular class label (AD). Class conditional feature estimation: Estimation of means and variances of features when given a class label.

4. Multinomial Naive Bayes: A probabilistic classifier that can be applied to frequency or count-like classification tasks in which feature vectors are a histogram of the components of FCTH as feature frequencies. It is particularly useful for the histogram-like descriptors where the number of bins is related to the frequencies of features.

5. k-Nearest Neighbors (k-NN): Classifies an MRI image to the maximum class of the k nearest neighbours in the FCTH feature space according to the Euclidean distance in feature space.

6. Radius Neighbours: The same as nearest neighbour classification but with neighbourhood size that varies according to the feature density rather than a fixed number k and radius R that is defined in FCTH feature space.

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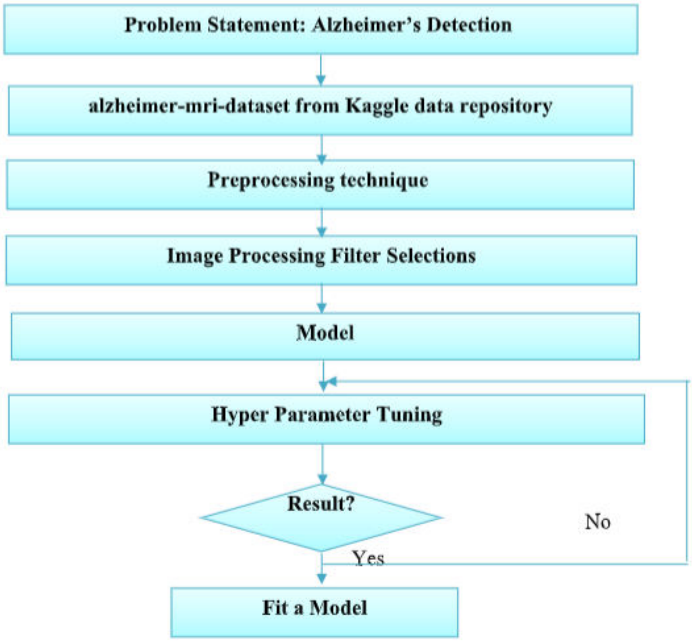

Figure 1: Proposed System

These metrics were used to compare and analyze the effectiveness of each classifiers.
Calculation of statistically relevant results was made possible through 10-fold cross-validation in the experiments. The classification performance evaluation used standard metrics for assessment.

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- ROC
- PRC

IV. EXPERIMENTAL RESULTS

Table 1 presents the complete classification performance of all six FCTH-based classifier combinations on the Alzheimer's MRI Dataset test set.

Table 1: Classification Metrics

Category	Classifier	Accuracy	Precision	Recall	ROC	PRC	Time (In Sec)
Linear	FCTH Filter + Logistic Regression	78.17	0.77	0.76	0.84	0.82	15.12
Linear	FCTH Filter + Ridge Classifier	84.23	0.83	0.82	0.89	0.82	11.15
Linear	FCTH Filter + Gaussian Naive Bayes	82.31	0.81	0.80	0.88	0.80	12.24
Linear	FCTH Filter + Multinomial Naive Bayes	85.11	0.84	0.84	0.90	0.88	3.21

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Linear	FCTH Filter + k-Nearest Neighbors	84.21	0.83	0.83	0.89	0.87	2.35
Linear	FCTH Filter + Radius Neighbors	80.13	0.79	0.78	0.86	0.84	6.65

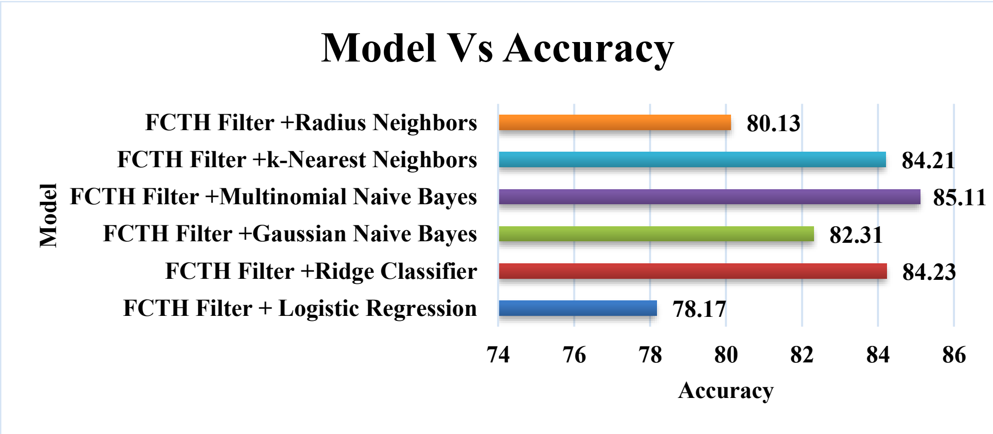

Figure 2: Model Vs Accuracy

The accuracy chart shows clearly that there are two levels of performance. The top 3 all achieve results above 84%, and are within 0.90% of each other suggesting that these classifiers are statistically near equivalent. To the mid-tier accuracy, FCTH+Gaussian Naive Bayes (82.31%) and FCTH+Radius Neighbors (80.13%) algorithms have, respectively, 4.14% and 2.02% less accuracy than the top performer.To mid-tier accuracy, FCTH+Gaussian Naive Bayes (82.31%) and FCTH+Radius Neighbors (80.13%) algorithms have, respectively, 4.14% and 2.02% less accuracy than the top performer. The x-axis baseline at 74% emphasizes the visual difference; the actual accuracy difference between the classifiers ranges from 6.94% at the 74% baseline, which is meaningful for a neuroimaging multi-class task.

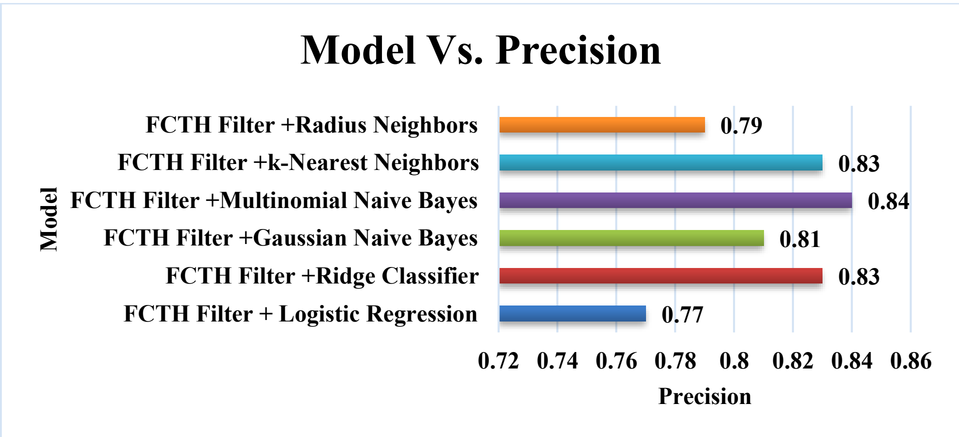

Figure 3: Model Vs Precision

Precision values range from 0.77 to 0.84, with the best precision being attained by FCTH+Multinomial Naive Bayes with a precision of 0.84, meaning it makes the least number of false positive AD class predictions per 100 positive predictions. The second tier, following best seen by the FCTH Classifier and the FCTH+kNN with a score of 0.83. At 0.77, the FCTH+Logistic Regression model has the lowest precision of the classifiers, meaning that about 23 of the 100 positives predicted by this model are actually false positives, the highest false positive count for the classifiers used in

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the experiment. The 0.07 range of precision indicates that meaningful differentiation of classifiers in the feature space FCTH.

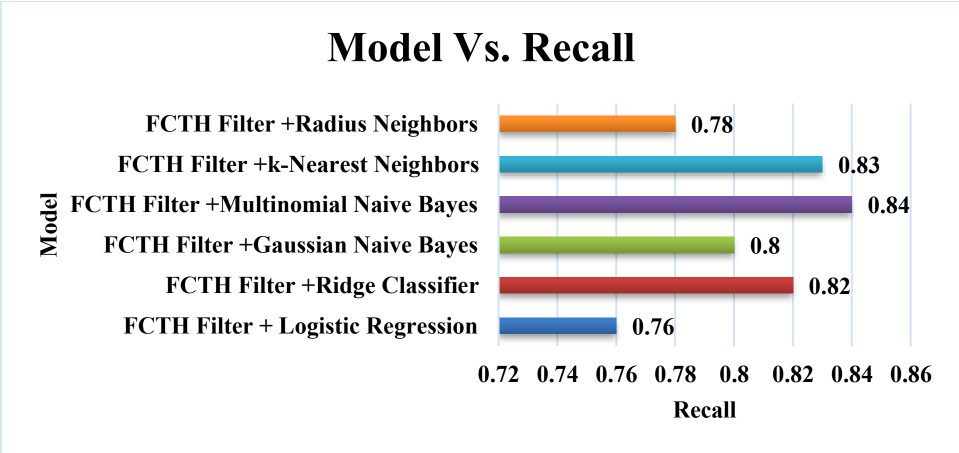

Figure 4: Model Vs Recall

When it comes to the most clinically important Alzheimer's screening test statistic, Recall, FCTH+Multinomial Naive Bayes is ahead at 0.84, correctly identifying the largest percentage of true AD cases. FCTH+k-Nearest Neighbors is the second most sensitive classifier with a score of 0.83. The recall of both FCTH+Gaussian Na Bayes and FCTH+Radius Neighbors is 0.80. The lowest was achieved by FCTH+Logistic Regression at 0.76, with about 24% missed cases of true AD in the test set, which is not acceptable in a screening application. The overall performance of all classifiers (except Logistic Regression) is greater than 0.80 in terms of recall, meaning FCTH features generally have the ability to capture MRI texture information that is most discriminative for AD.

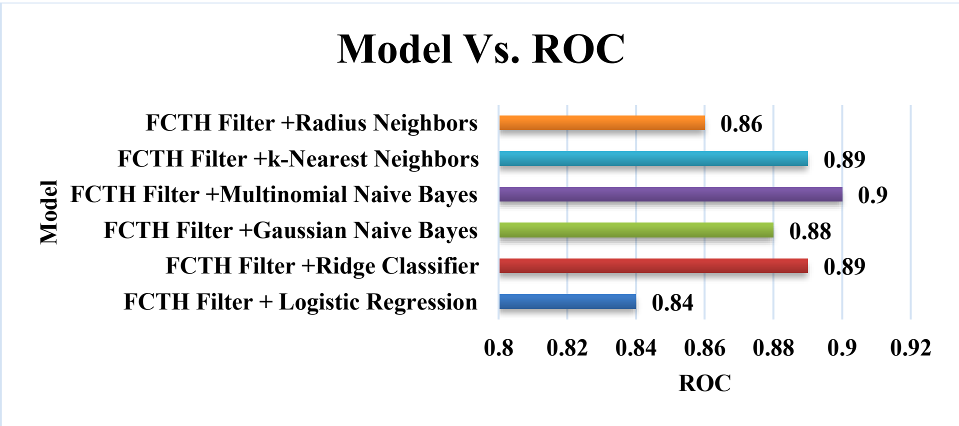

Figure 5: Model Vs ROC

The ROC area is the best indicator of the difference between classifiers. FCTH+Multinomial Naive Bayes is the best classifier with the highest ROC area of 0.90 (the only one that reaches the 0.90 level), which indicates that this classifier is able to discriminate between classes very well in the FCTH feature space. FCTH+Ridge Classifier and FCTH+k-Nearest Neighbors both get ROC = 0.89, and are a solid second tier. FCTH+Gaussian Na Bayes has a score of 0.88, followed by FCTH+Radius Neighbors (0.86) and FCTH+Logistic Regression (0.84). The ROC values for all six classifiers are greater than 0.84, indicating that FCTH features offer good Alzheimer's class separability with all algorithmic approaches tested [7].

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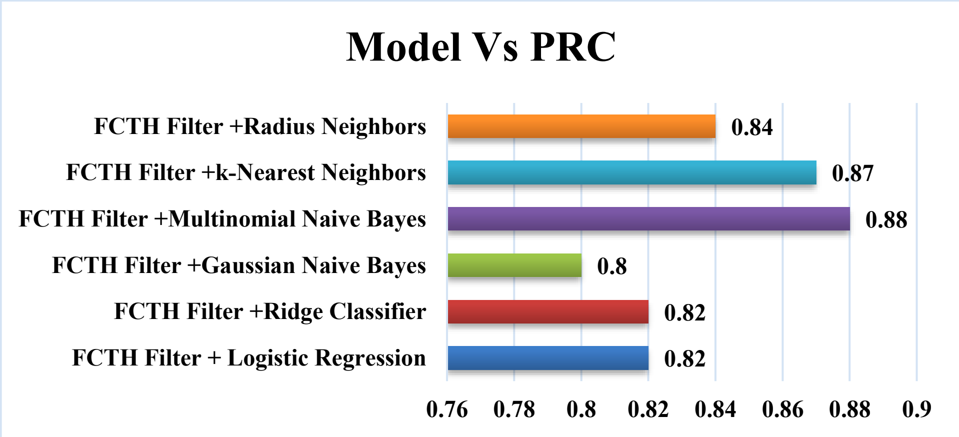

Figure 6: Model Vs PRC

There is a significant difference from the ROC pattern that is indicated by the area of the Precision-Recall Curve. FCTH+Multinomial Naive Bayes outperforms the other classifiers on PRC, with a score of 0.88, while FCTH+k-Nearest Neighbors ties for second place with a score of 0.87 — even if the precision-recall balance is tied across all thresholds. FCTH+Radius Neighbors achieves a PRC of 0.84 compared to FCTH+Ridge (0.82) and FCTH+Logistic Regression (0.82), while having a lower overall accuracy, indicating that Radius Neighbors is more effective at a non-default threshold on the precision-recall curve. The lowest PRC is obtained by FCTH+Gaussian Na Bayes, which indicates that its Gaussian distribution assumption is the least suitable for FCTH's fuzzy histogram feature structure.

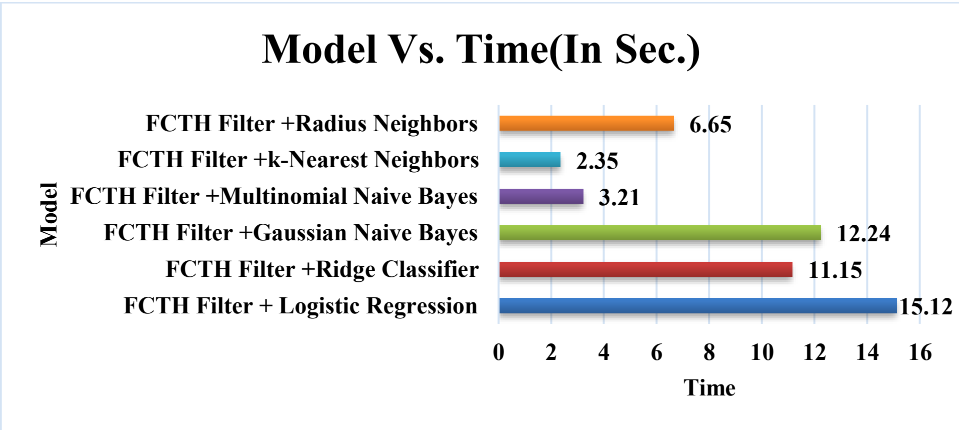

Figure 7: Model Vs Time (In Sec.)

The training time chart shows the most significant difference in the experiment with the fastest and slowest classifiers being almost 13 seconds apart. The most time efficient two classifiers are FCTH+k-Nearest Neighbors with a training time of 2.35 seconds, and FCTH+Multinomial Naive Bayes with a training time of 3.21 seconds. The training costs of FCTH+Radius Neighbors (6.65 s), FCTH+Ridge (11.15 s), FCTH+Gaussian Naive Bayes (12.24 s) and FCTH+Logistic Regression (15.12 s) are progressively higher.

V. CONCLUSION

The Fuzzy Color and Texture Histogram (FCTH) Filter is a novel image feature extraction technique that is systematically assessed as an automatic classification method for Alzheimer's disease from MRI images in this study employing six machine learning classifiers on Alzheimer's MRI Dataset from Kaggle. The best performing configuration (FCTH+Multinomial Naive Bayes) yielded an overall accuracy of 85.11%, a precision of 0.84, a recall of

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0.84, an ROC area of 0.90, and a PRC area of 0.88, the highest number for all measures 1–2, demonstrating its optimal performance in Alzheimer's classification using MRI in terms of both discriminative accuracy and threshold-independent measures. This configuration, FCTH+k-Nearest Neighbors, was the most computational efficient with a training time of 2.35 seconds, also had the best accuracy (84.21%) and the second largest PRC area (0.87), which was preferable for screening MRIs in a high throughput environment for real-time Alzheimer's diagnosis. The superior performance of Multinomial Naive Bayes over the other classifiers was attributed to the structural compatibility with FCTH's feature representation, where the feature representation is done in a histogram based approach, and thus the development of medical image classification pipeline is greatly influenced by feature-classifier alignment [7]. Future research directions include: (i) enriching the representation of the neuroimaging data with complementary descriptors like the GLCM texture features [12] and volumetric morphometric features; (ii) mapping the importances of the FCTH bins to specific neuroanatomical regions involved in Alzheimer's pathology, using explainable AI techniques; (iii) evaluating the FCTH features on multi-site, multi-scanner MRI datasets to assess cross-scanner generalizability; and (iv) comparative benchmarking with deep learning feature extractors [9,10] on larger annotated Alzheimer's MRI corpora. This study develops an FCTH+Multinomial Naive Bayes framework that offers a baseline solution for automated Alzheimer's MRI classification for reproducibility, computability, and near clinical deployment.

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