OPEN ACCESS
International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-15 Issue-1, October 2025

Alzheimer Classifications Combining Machine Learning and Signal Processing

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Abstract: ***Manual detection of presence of Alzheimer even determination of its intensity from Magnetic Resonance Imaging (MRI) image is an easy task when a patient is heavily affected by the disease. The situation becomes cumbersome for a physician when a very mild affected image comes under consideration. For cases involving subtle differences in images, Machine Learning (ML) and Deep Learning (DL) classification are considered the best solutions. In this paper, Alzheimer-affected images of four categories —mild impairment, moderate impairment, very mild impairment, and no impairment — are taken from a benchmark open database. The image set is converted to a numerical feature vector using Speeded-Up Robust Features (SURF), Features from Accelerated Segment Test (FAST), Harris–Stephen's, and minimum eigenvalue. The feature vector is then applied to several ML algorithms: Fuzzy Inference System (FIS), Multiple Linear Regression (MLR), Fuzzy C-Means (FCM), Naïve Bayes and linear Support Vector Machine (SVM) to check their eligibility in classifying these four types of medical images. The accuracy of detection from any individual method ranges from 56% to 68%. However, applying the maximum voting scheme to all the MLs yields an accuracy of 75%. The long feature vector is also extracted from the discrete wavelet transform (DWT), and classification is done from its coherence, but the accuracy is found to be very poor. Next, the image dataset is applied to the Bag of Features (BoF) algorithm using 500 visual words, yielding a moderate result with an accuracy of 84.28%. Finally, two deep learning models are applied: PyTorch Convolutional Neural Network (CNN) and Keras Visual Geometry Group (VGG) 19. These models are tested on 20% of the trained images, achieving accuracies of 95.7% and 97.1%, respectively.***

Keywords: ***BoF, Accuracy, Coherence of DWT, FIS, and Parallel Plot.***

Abbreviations:
AD: Alzheimer's disease
CNNs: Convolutional Neural Networks
MCI: Mild Cognitive Impairment
MLR: Multiple Linear Regression
CN: Cognitively Normal
MRI: Magnetic Resonance Imaging
VMD: Very Mild Dementia
MoD: Moderate Dementia
LSTM: Long Short-Term Memory
DL: Deep Learning
ML: Machine Learning
SURF: Speeded-Up Robust Features
FIS: Fuzzy Inference System
BoF: Bag of Features

Manuscript received on 23 May 2025 | First Revised Manuscript received on 30 May 2025 | Second Revised Manuscript received on 17 September 2025 | Manuscript Accepted on 15 October 2025 | Manuscript published on 30 October 2025.

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I. INTRODUCTION

The brain is considered one of the most pivotal organs in the human body. All the activities and responses that allow us to think and believe are administered and facilitated by the brain. It also empowers our attitude and recollections. Alzheimer's Disease (AD) is an incurable, progressive neurological brain disorder (eg, memory loss). It happens when plaques containing beta amyloid protein form in the brain. Every three seconds, someone in the world is diagnosed with Alzheimer's disease. According to the World Alzheimer's report statistics, People over the age of 65 are most likely to get this condition. More than 55 million people have been diagnosed with Alzheimer's disease, and this number is increasing day by day, with 78 million expected by 2030, as shown in [1].

The patient will forget current events in the early stages. If the illness progresses, they will moderately forget whole events. It is indispensable to diagnose the disease as soon as possible. Initial detection of Alzheimer's disease can help with proper treatment and prevent brain tissue damage. There is no cure for this condition, but modern medications and treatments are available to slow down the disease progression temporarily. AD can be more precisely categorised using segmented MRI scans due to in-depth analyses of tissue architecture. Several complex segmentation approaches have been proposed for Alzheimer's disease (AD) diagnosis. Since machine learning algorithms can yield effective results over an extensive data collection, they have received interest for use in segmenting the brain's structure and classifying AD.

The rest of the paper is organized as: section II discusses about results of some recent works relevant to detection of levels of Alzheimer's affect, section III deals with methodology of this research work contains image processing, ML and DL to classify disease affected images, section IV provides the results using the method of the paper and section V concludes the entire paper with some future recommendations.

II. LITERATURE REVIEW

This section discusses some state-of-the-art works pertinent to image classification, specifically the identification of diseases from medical images. AD is the most common form of dementia. It typically manifests as a progressive decline in cognitive function and memory, subsequently impairing the person's ability to live independently and having a significant impact on both the affected individual and society, as noted in [2]. Ms. Ashwini. S. Shindea and Dr. Veena. V. Desaan discusses and implements various machine learning algorithms, including Naive Bayes, Logistic Regression, Multi-layer Perceptron, Support Vector Machine, and Decision Tree, to analyse brain tumours using MRI images [3].

In [4], authors used structural magnetic resonance imaging (sMRI) 1) to increase the accuracy level that is comparable to the state-of-the-art methods; 2) to overcome the overfitting problem, and 3) to analyse proven landmarks of the brain that provide discernible features for AD diagnosis. They focused specifically on both the left and right hippocampus areas of the human brain and then applied simple convolutional neural networks (CNNs) as feature extractors and soft-max cross-entropy as the classifier. In [5], the author provides a brief review of some critical literature on AD and explores how deep learning can aid researchers in diagnosing the disease at its early stages.

The data used from international challenge for automated prediction of MCI from MRI data to address the multiclass classification problem and a novel multiclass classification approach that addresses the outlier detection problem, uses pairwise t-test feature selection, project the selected features onto a Partial-Least-Squares multiclass subspace, and applies one-versus-one error correction output codes classification for detection of Alzheimer's Disease in its early stages is proposed in [6]. In the author studies, specific information in clinical text, including the age, sex and genes of the person and apolipoprotein E; the brain function is established using resting-state functional data (MRI) for the measurement of connectivity in the brain regions [7]. A specialised network of autoencoders is used in earlier diagnosis to distinguish between natural ageing and disorder progression. The proposed approach effectively incorporates biased neural network functionality, enabling reliable recognition of Alzheimer's disease.

In [7], a model is proposed that takes brain MRI sample images as input and determines whether a person has mild, moderate, or no Alzheimer's disease as output [8]. Vandana B.S. and Sathyavathi R. Alva proposed two methods. Radiological feature extraction using image processing and machine learning from MRI images and Analysis of Alzheimer's disease state by using a deep learning approach [9].

A deep learning-based method to extract valuable AD biomarkers from structural magnetic resonance imaging (sMRI) and classify brain images into AD, mild cognitive impairment (MCI), and cognitively normal (CN) groups. Adapted and trained convolutional neural networks (CNNs) on sMRI images of the brain from ADNI datasets available in online databases and proposed mechanism was used to combine features from different layers to hierarchically transform the images from magnetic resonance imaging into more compact high-level features and reduced number of parameters which reduces the computation complexity develop in [10]. In the authors develop a deep learning-based pipeline for the accurate diagnosis and stratification of Alzheimer's disease (AD) stages [11]. The analysis pipeline utilises a shallow Convolutional Neural Network (CNN) architecture and 2D T1-weighted Magnetic Resonance (MR) brain images to provide both global classification (i.e., standard vs. Mild Cognitive Impairment (MCI) vs. Alzheimer's disease (AD)) and local classification. The latter deals with an even more challenging task to stratify MCI into a Very Mild Dementia (VMD), mild dementia (MD), and Moderate Dementia (MoD) as the prodromal AD stage.

III. METHODOLOGY

In this section, three algorithms are introduced that are used to extract features from MRI images and facilitate their classification. The first and second algorithms are primarily used in object classification under image processing and computer vision. The third one is applicable in both agricultural and medical image classification, when very little difference is found among the classes.

A. Algorithm in determining feature table

i. Read an image and apply pre-process (denoise and resize) on it.
ii. Apply the SURF algorithm on the image and extract the value and location of the five most prominent (five consecutive points of highest strength) feature points.
iii. From the points (x_i, y_i), i =1, 2, 3, 4, 5; select the point (x_h, y_h) of maximum scale.
iv. Determine the Euclidian distance between (x_h, y_h) and (x_i, y_i) as: $d_i = \sqrt{(x_h - x_i)^2 + (y_h - y_i)^2}$, $i \neq m$.
v. Sort the Euclidean distances, d_i and put them in a vector, $\mathbf{D}_{SURF} = [d_1\ d_2\ d_3\ d_4]$.
vi. Create a table of vector $\mathbf{D}_{SURF}$ for four types of images.
vii. Apply steps 1 to 6 on using 'corners feature extraction using FAST algorithm'.
viii. Apply steps 1 to 6 on using 'corners feature extraction using Harris–Stephen's algorithm'.
ix. Apply steps 1 to 6 on using 'corners feature extraction using minimum eigenvalue algorithm'.
x. Apply FIS, MLR, Naïve Bayes, SVM and FCM on the complete table.

B. Algorithm in Determining Coherence of Two Images using DWT

Read the image **I** of class-1

Select the dimension of the image as N

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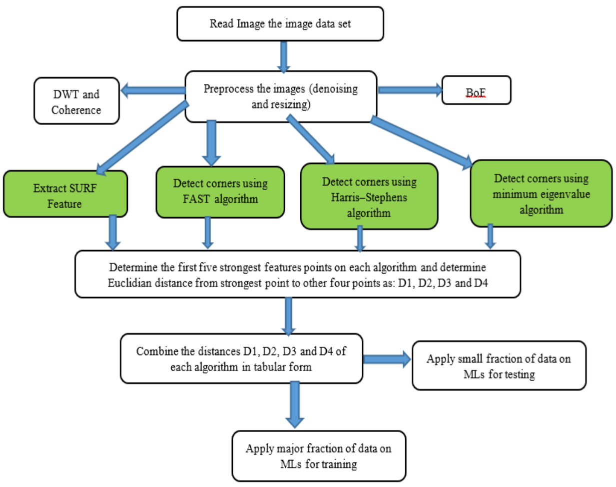
Resize the image as: $N \times N$
for i = 1: N,
$\mathbf{S}_i$ = ith row of the image
for i=1 to N
while length(y)>1
y= dwt ($\mathbf{S}_i$); % continue the DWT until the length of y is 1.
end%end of while loop
$r(i) = y$; % ith element/row of the column vector
end % end of for loop
while length(r) > 64
r = dwt(**r**); % continue the DWT until the length of r is 64
end
$\mathbf{v}_1$ = **r**;
% vector with the lowest frequency of image **I** of class-1
determine $\mathbf{v}_2$ the vector with the lowest frequency of image **I** of class-2
$\mathbf{C}_{12}$ = coherence ($\mathbf{v}_1$, $\mathbf{v}_2$);
% The coherence of the image of class-1 and class-2

C. MLs in image Classification

The entire operation of the training or test phase of 'classification of Alzheimer MRI image' used in this paper is shown in Fig. 1.



[Fig.1: Entire Operation of Image Classification (Training or Test)]

Two deep learning models, CNN and its variant VGG-19, are also applied for classifying Alzheimer's images to achieve better results. However, image processing and machine learning algorithms are tried first to obtain reasonable results with less processing time. The image data set of the paper is collected from Kaggle's open and free dataset under the project: 'Alzheimer_MRI_Detection_Densenet_PyTorch' with URL: *https://www.kaggle.com/code/alibidaran/alzhaimer-mri-detection-densenet-pytorch/input*.

IV. RESULT AND DISCUSSIONS

First, the four strongest features are taken under four algorithms: (i) SURF of [12], (ii) Corners Features using FAST algorithm, (iii) Corners Features using Harris–Stephen's algorithm, and (iv) Corners Features using minimum eigenvalue algorithm of [13]. For each category, 400 records are extracted, and among them, 350 are taken for training, and the remaining 50 records are used for validation. Few records are shown in table I, II, III and IV against four algorithms.

Table- I: SURF Records

SURF				Category
SURF1	***SURF2***	***SURF3***	***SURF4***	
29.04	57.83	61.84	95.38	Mild Impairment
61.16	118.89	135.27	154.93	Moderate Impairment
48.81	59.01	108.27	156.10	Very Mild Impairment
0.96	53.89	98.21	124.17	No Impairment
29.59	30.29	77.21	109.55	Mild Impairment
8.05	27.75	65.79	118.56	Moderate Impairment
22.42	61.09	134.51	154.05	Very Mild Impairment

Table- II: Records of Corners Features using FAST Algorithm

Corners Features using FAST algorithm				Category
FAST1	***FAST2***	***FAST3***	***FAST4***	
40.70	67.20	70.03	89.14	Mild Impairment
68.15	75.01	87.59	111.00	Moderate Impairment
10.29	145.60	180.23	197.64	Very Mild Impairment
20.24	66.18	86.35	96.67	No Impairment
2.83	35.01	42.30	216.02	Mild Impairment
41.18	53.14	106.71	171.64	Moderate Impairment
34.13	74.25	139.85	142.41	Very Mild Impairment

Table-III: Records of Corners Features using Harris–Stephen's Algorithm

Corners Features using Harris–Stephen's algorithm				Category
HS1	***HS2***	***HS3***	***HS4***	
75.42	107.25	120.64	125.90	Mild Impairment
4.50	150.80	165.42	186.43	Moderate Impairment
52.03	143.45	144.84	148.47	Very Mild Impairment
34.06	97.00	97.89	100.88	No Impairment
58.35	198.24	205.65	211.68	Mild Impairment
74.28	76.08	90.19	116.11	Moderate Impairment
55.44	59.77	72.94	155.65	Very Mild Impairment

Table- IV: Records of Corners Features using Minimum Eigenvalue Algorithm

Corners Features using minimum eigenvalue algorithm				Category
EIG1	***EIG2***	***EIG3***	***EIG4***	
9.51	65.76	69.70	90.46	Mild Impairment
21.61	110.24	147.67	150.36	Moderate Impairment
51.41	93.50	194.35	198.57	Very Mild Impairment
70.38	72.81	87.19	101.66	No Impairment
58.13	197.93	205.68	210.93	Mild Impairment
36.88	45.18	72.98	100.17	Moderate Impairment
55.40	59.66	73.11	155.89	Very Mild Impairment

The 'parallel coordinate plots' of the data points are shown in Fig. 2 (a) and (b) for 8 and 16 features, respectively. Such a plot is primarily used to visualise higher-dimensional (usually more than three-dimensional) data points. Enormous overlap is found in the plot, and the points are also highly uncorrelated. The phenomenon is also visualised from the scattered plot of Figure. 3(a) and (b), where only two variables are considered. The AUC from the ROC of the four classes of images is found to be less than 60%, as shown in fig. 4. It will be difficult to segregate pictures from a Single ML. Under these adverse conditions, we will apply different approaches to classify four types of images using feature data points (or records).

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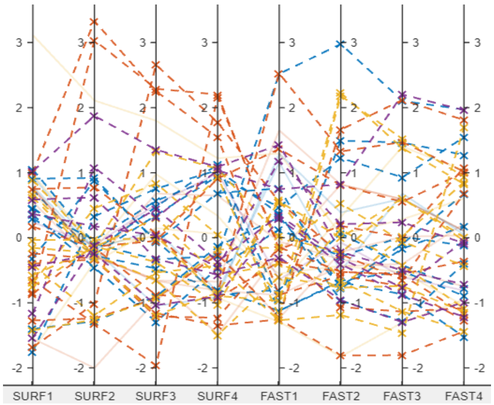
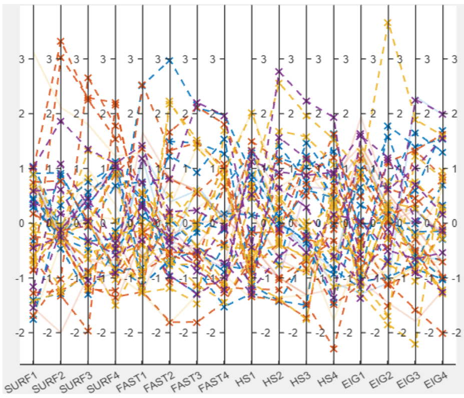
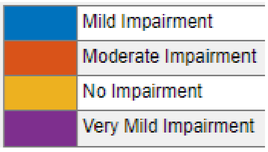


(a)Eight Feature Points

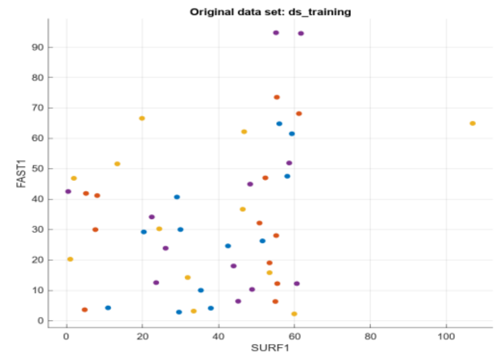


(b) Sixteen feature points

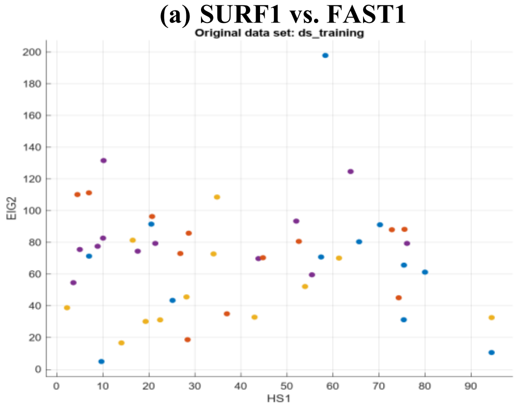


(c) Legends

[Fig.2: Parallel Plot of Feature Points]

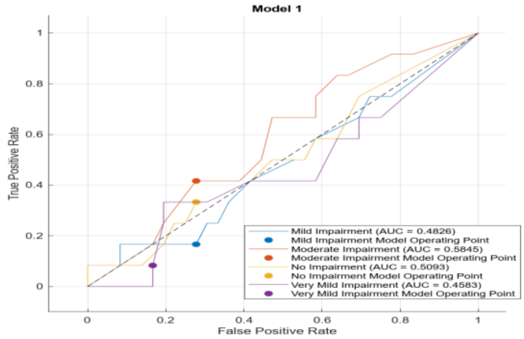


(a) SURF1 vs. FAST1



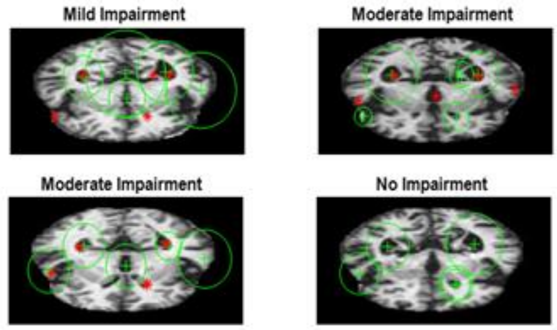
(b) HS1 vs. EIG1

[Fig.3: Scattered Plot of Data Points for Two Cases]

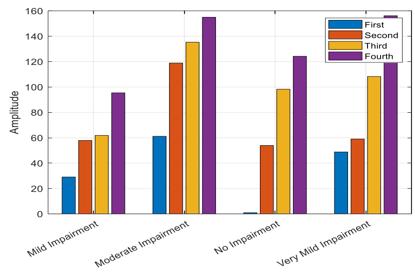


[Fig.4: ROC of Four Categories of Data]

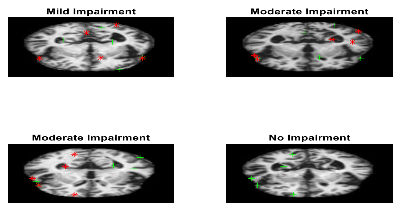
The next part of the result deals with the Euclidean distance between feature points on the image. First, the five strongest SURF feature points are selected on each of the four types of images shown in Fig. 5(a). The Euclidean distance between 'the point of lowest value' and the other four points is evaluated, then sorted. The four sorted distances are shown in the bar graph of Fig. 5(b). Similar images and graphs are shown for 'Corners Features points using FAST algorithm' in the figure. 5(c)-(d), image and graph for 'Corners Features points using Harris–Stephen's algorithm' case are shown in Fig. 5(e)-(f), and those of 'Corners Features points using minimum eigenvalue algorithm' are shown in Fig. 5(g)-(h).



(a) SURF Feature Points



(b)Bar of Euclidian distances



(c) Corners Features Points using FAST Algorithm

Retrieval Number: 100.1/ijeat.E467314050625
DOI: [10.35940/ijeat.E4673.15011025](https://doi.org/10.35940/ijeat.E4673.15011025)
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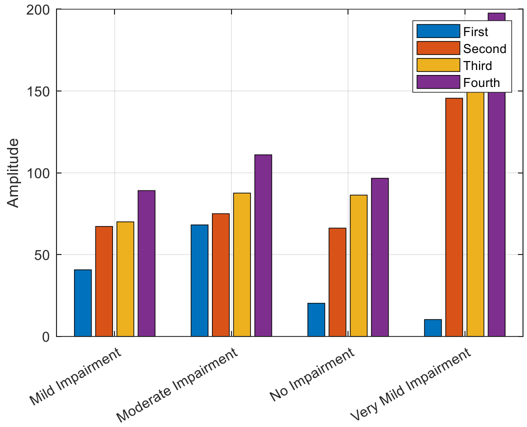
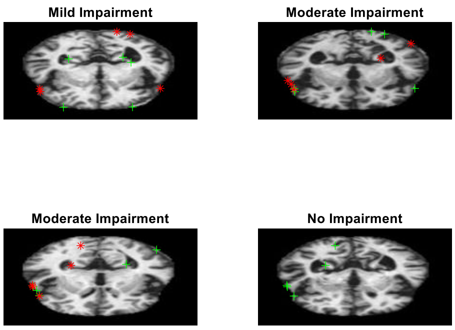
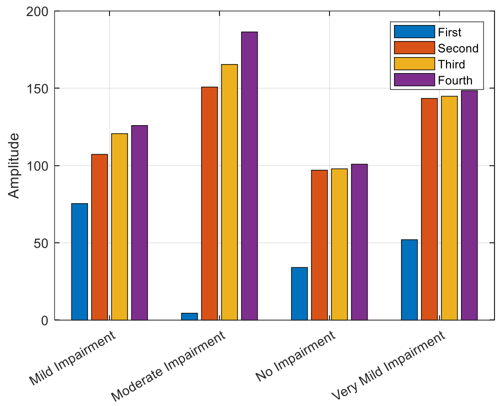


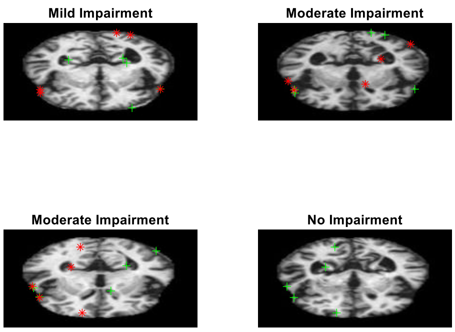
(d) Bar of Euclidian distances



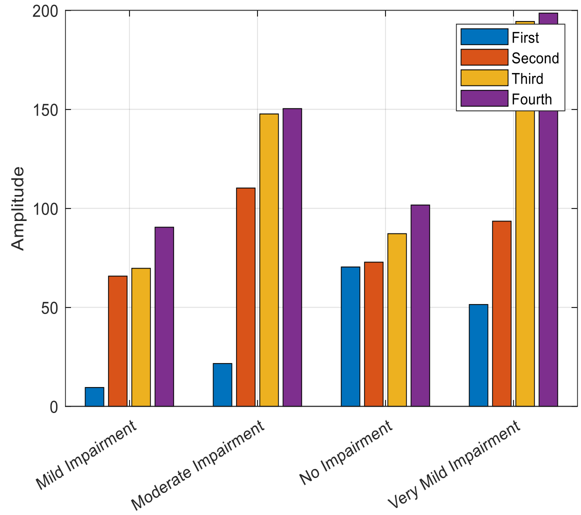
(e) Corners Features Points using Harris–Stephens Algorithm



(f) Bar of Euclidean Distances



(g) Corners Features Points using Minimum Eigenvalue Algorithm

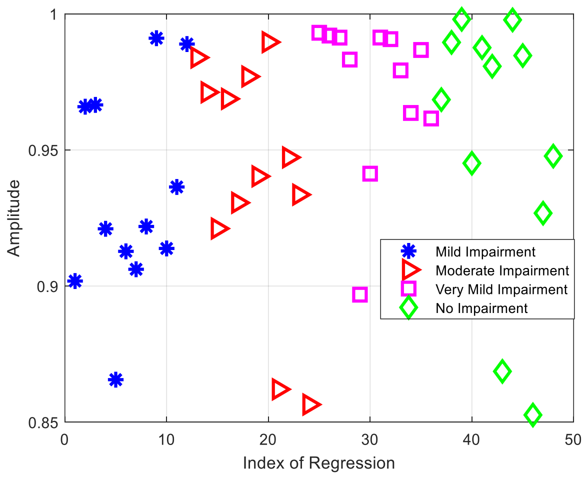


(h) Bar of Euclidean Distances

Fig.5: Features of Four Types of Images

The MLR is applied to the entire data set of four classes, and the result is shown in Fig. 6. Since the amplitude has very low variation, the data set has Very low correlation, and MLR reveals abysmal performance. Next, we applied FIS (Mamdani rule with centroid method of defuzzification) on the previous dataset. The results of the four-test data are shown in the figure. 7(a)-(d) against four class. The performance is deemed poor by the FIS.

Finally, FCM (fuzzy c-means clustering) is applied to the complete data set. The corresponding result is shown in Fig. 8(a), where the data points of the four classes are distributed randomly, and the centres of the classes are very close; hence, FCM also fails to provide good performance. The cost function of FCM becomes fixed at a very high value, as shown in Fig. 8(b).



[Fig.6: Results of MLR]

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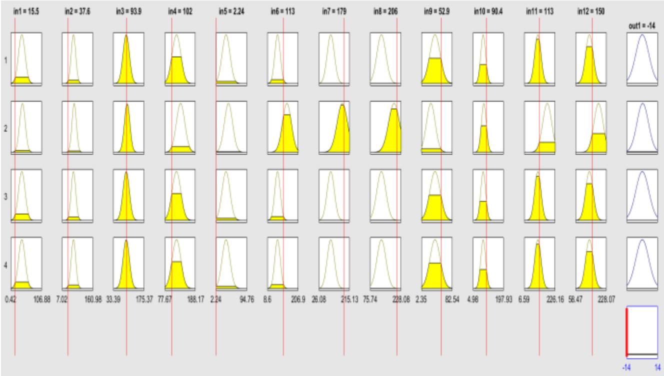
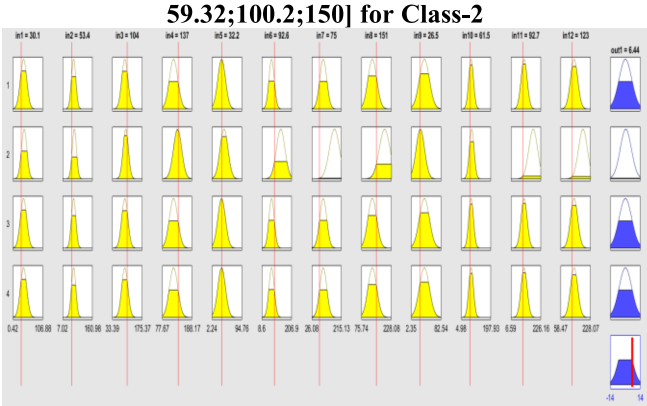
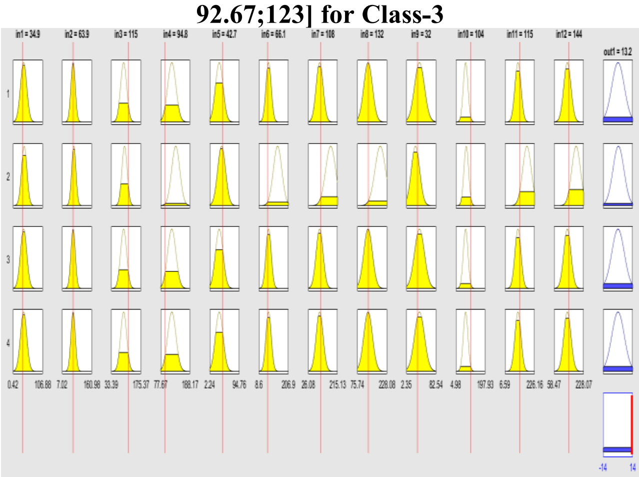


(a) Input Vector, v = [15.54;37.64;93.89;102.4;2.24;113.4;179.3;206.4;52.92; 90.37;112.6;150] for Class-1

(b) Input Vector, v = [47;56.88;72.92;102.4;50.08;66.03;120.6;159.7;53.84; 59.32;100.2;150] for Class-2

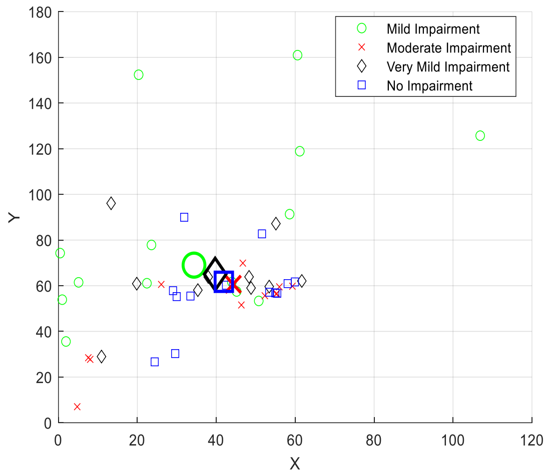


(c) Input Vector, v = [30.06;53.38;103.6;136.7;32.2;92.63;74.97;151;26.5;61.5; 92.67;123] for Class-3

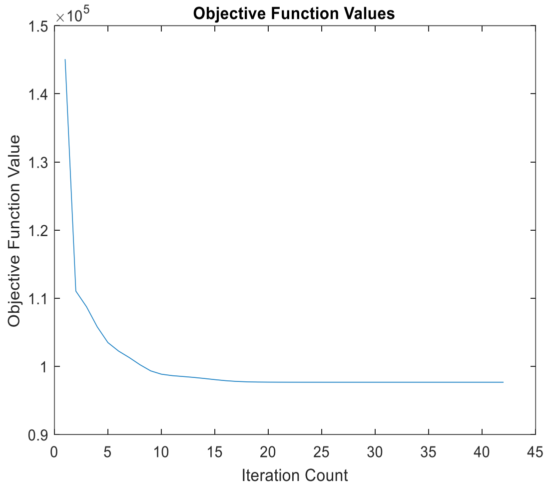


(d) Input Vector, v = [34.9;63.88;114.9;94.82;42.72;66.06;107.6;132;31.97; 103.7;115.1;144.2] for Class-4

[Fig.7: Results of FIS From the Table of Four Attributes]



(a) Data Points of FCM



(c) Profile of the Objective Function

Fig.8: Performance of FCM on Classification of Four Classes]

Next, a one-dimensional DWT is applied to each row of the image until it is reduced to a single point. The entire image becomes a column vector, and then a one-dimensional DWT is applied to the column vector to reduce its size to 1×64. The resultant column contains the few lowest and prominent frequency components of the image. First, the idea is applied to 'Moderate Impairment' and 'no Impairment' images, then wavelet coherence is applied to them to find the phase difference between them. The corresponding results are shown in fig.9 for three cases. Very little difference in phase is found only at medium and high frequency. The profile of the discrete plot also has a minimal difference. Similar results are shown for the case of 'Mild Impairment' and 'Very Mild Impairment', as shown in Fig. 10. The expected difference on the coherence graph is also found to be very poor for this case. Such a slight difference is not applicable in image classification; however, the above concept is widely used in many object classification applications under image processing, as discussed in [14].

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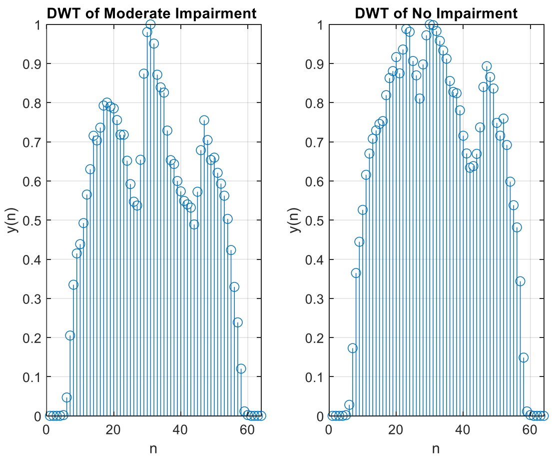
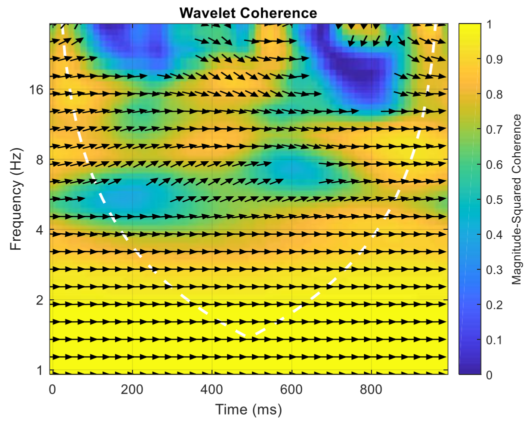
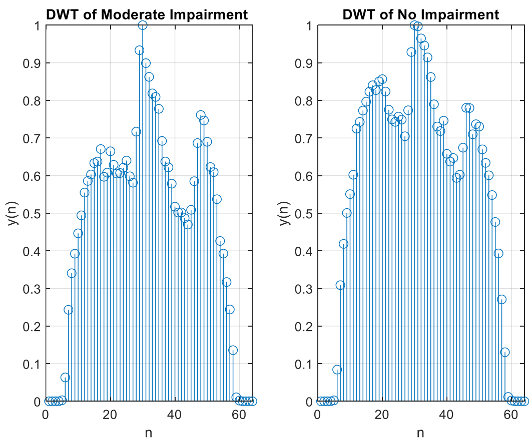


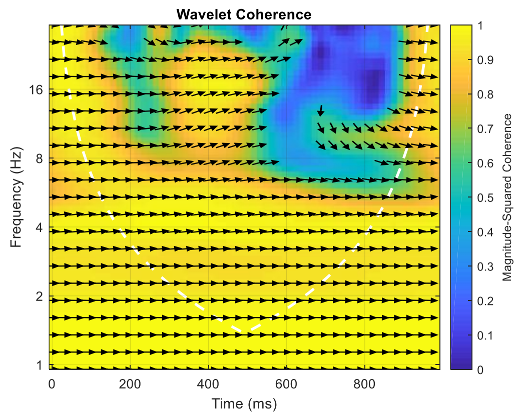
(a) DWT Components (Experiment-1)



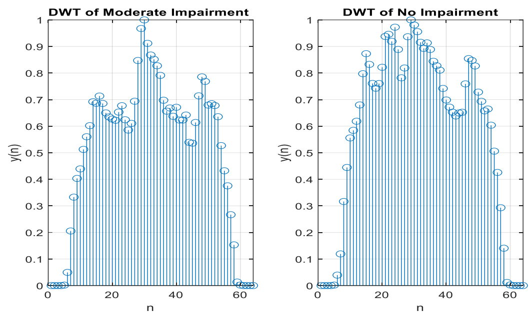
(b) DWT Coherence (Experiment-1)



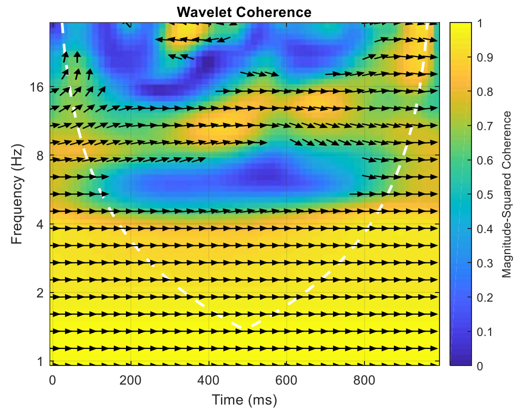
(c) DWT Components (Experiment-2)



(d) DWT Coherence (Experiment-2)

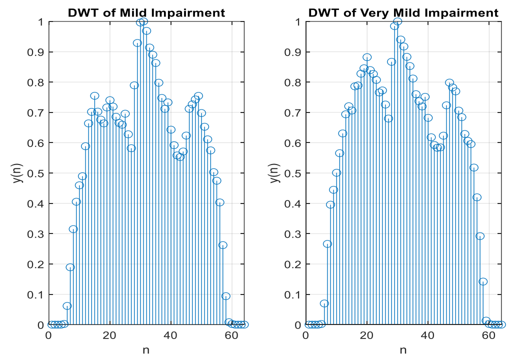


(e) DWT Components (Experiment-3)

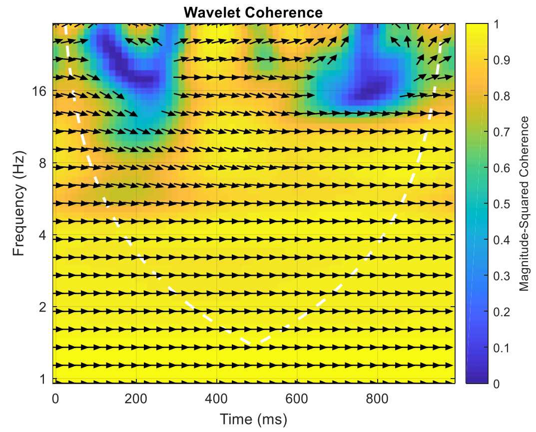


(f) DWT Coherence (Experiment-3)

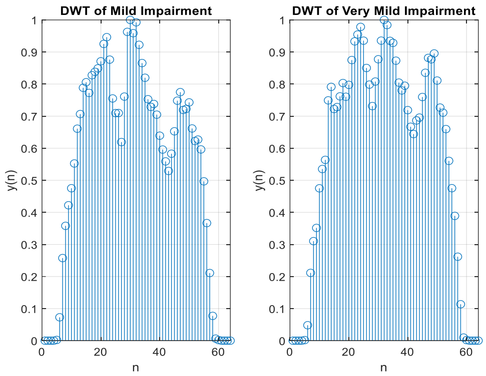
[Fig.9: DWT Components and Their Coherence]



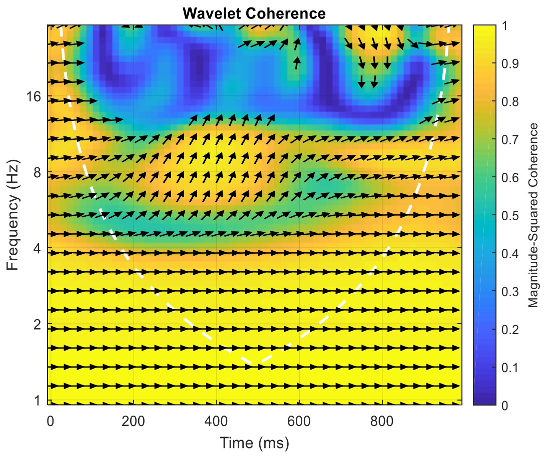
(a) DWT Components (Experiment-1)



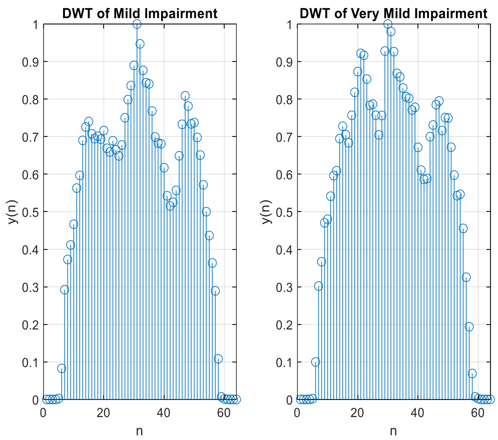
(b) DWT Coherence (Experiment-1)



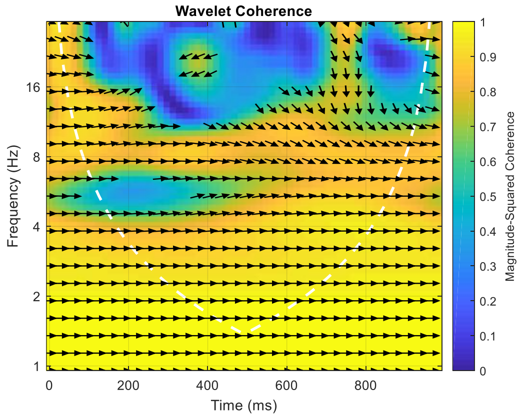
(c) DWT Components (Experiment-1)



(d)DWT Coherence (Experiment-1)



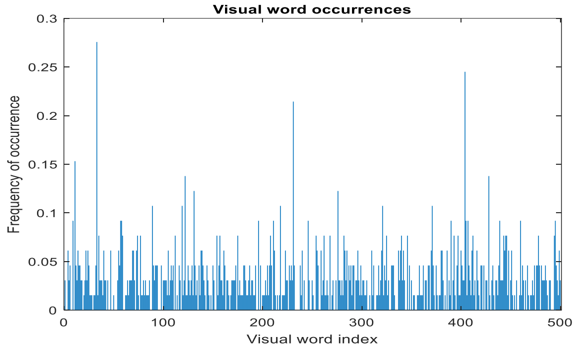
(e) DWT Components (Experiment-1)



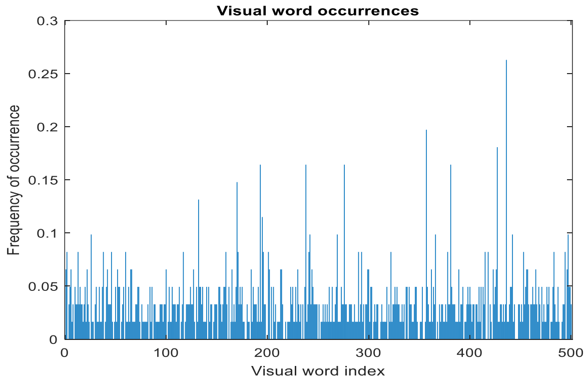
(f) DWT Coherence (Experiment-1)

[Fig.10: DWT Components and Their Coherence]

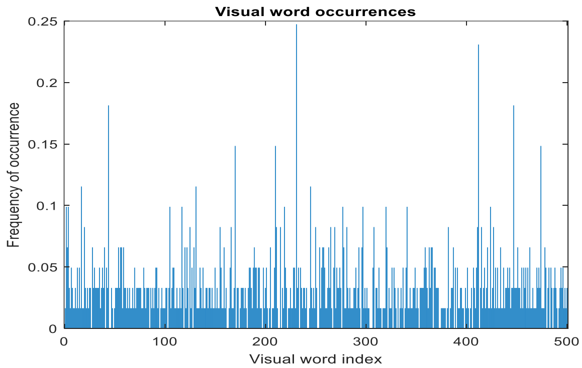
Next, 100 images per class are used in BoF, with 80% allocated for training and 20% for testing. The program is run three times, and the corresponding frequency of visual code words is shown in Fig. 11(a)-(c). The heat map of the bag of features against three experiments is shown in Fig. 12 (a)-(c). The detection of 'No Impairment' is found above 95%, and that of 'Moderate Impairment' is found near 85%. The 'Mild Impairment' showed poor results, i.e. near 60%, and the case of 'Very Mild Impairment' showed inferior results, near 10%. The reason behind the case is that both the 'Mild Impairment' and 'Very Mild Impairment' cases are very close to the case of 'No Impairment', but the 'Moderate Impairment' image has a wide variation from the image of the 'No Impairment' case. Finally, the performance of BoF is measured by taking 2560 images per class (80% training and 20% test).



(a) Experiment-1



(b)Experiment-2



(c) Experiment-3

[Fig.11: Visual Code Words of Bag of Feature Taking 4×100 Images]

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DOI: 10.35940/ijeat.E4673.15011025
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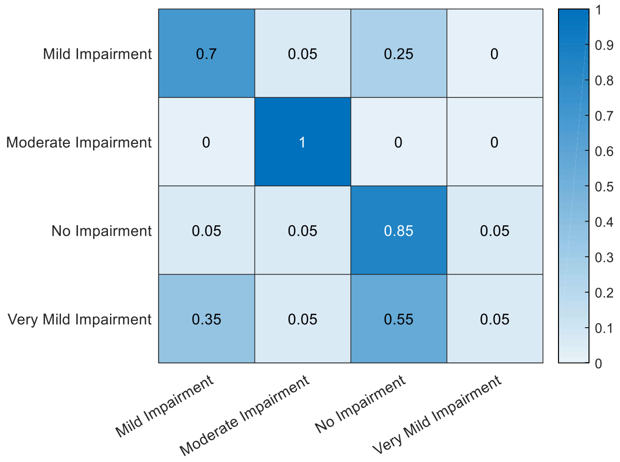
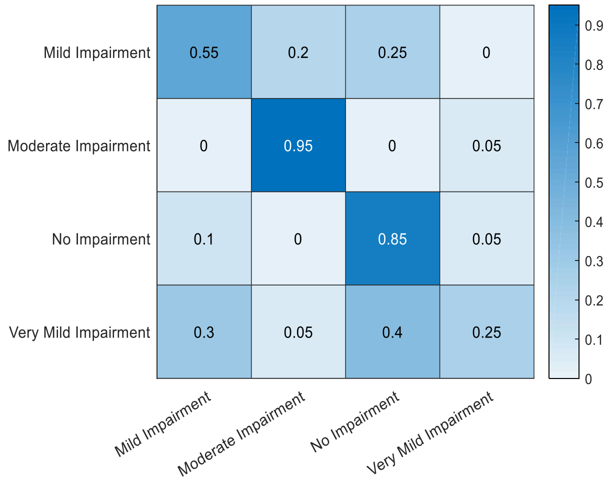
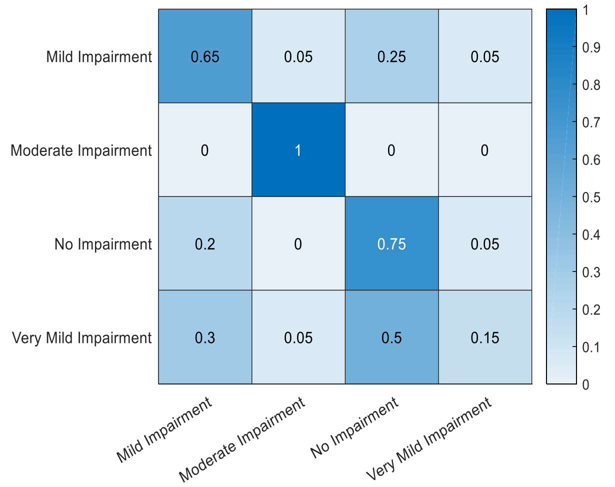


(a) Experiment-1



(b) Experiment-2

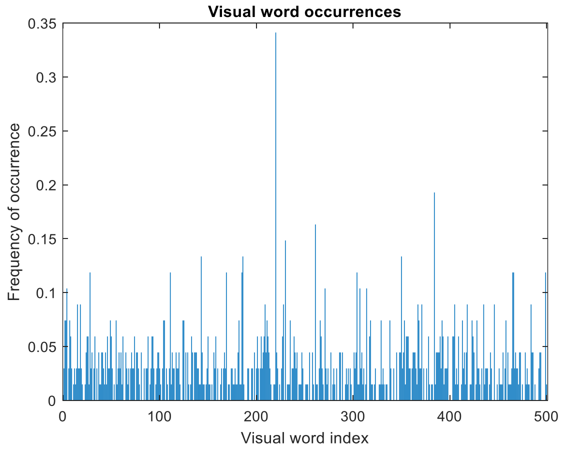


(c) Experiment-3

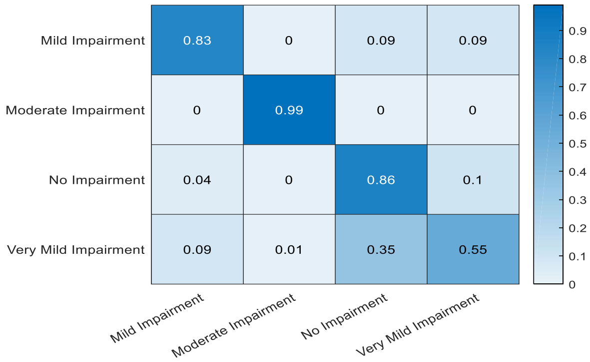
[Fig.12: Heat-Map of Bag of Features Taking 4×100 Images]

The BoF code extracted 8388608 features from 8192 images, where the *K*-Means clustering was used to create a 500-word visual vocabulary, and the number of clusters was set to $k = 500$.

The average accuracy is now improved to 81%, and the inferior component ''Very Mild Impairment' also improved considerably, as shown in fig. 13.



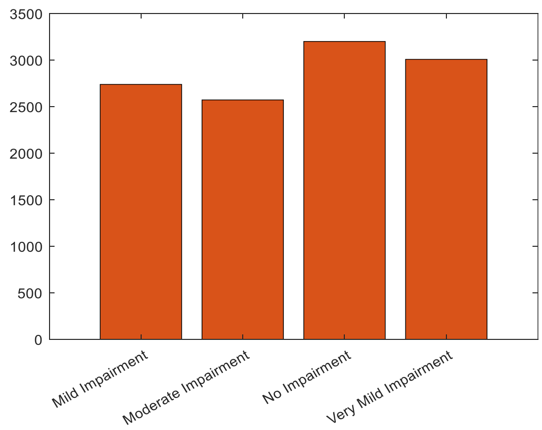
(a) Visual code words of a bag of feature



(b) Heat-map of a bag of Feature

[Fig.13: Performance of BoF Taking 4×2560 Images]

The four types of images, each with a size of 2739, 2572, 3200, and 3008, as shown in the bar graph of Fig. 14, are used for deep learning (DL), where 80% of the images are used for training and 20% for testing under PyTorch CNN and Keras VGG. Taking size of image 224*224, learning rate = 0.001, number of epochs = 10, batch size = 32, number of features=32 and kernel size=3 at both convolution layer we got the accuracy of 95.7% for PyTorch CNN and 97.1% for keras VGG. The confusion matrices of the test images are shown in Fig. 15(a) and (b).



[Fig.14: Number of Images of Four Categories]

Retrieval Number: 100.1/ijeat.E467314050625
DOI: 10.35940/ijeat.E4673.15011025
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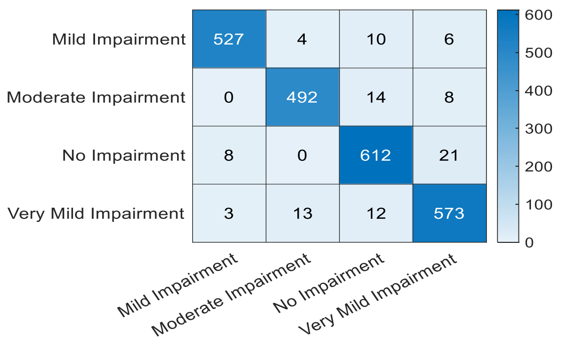
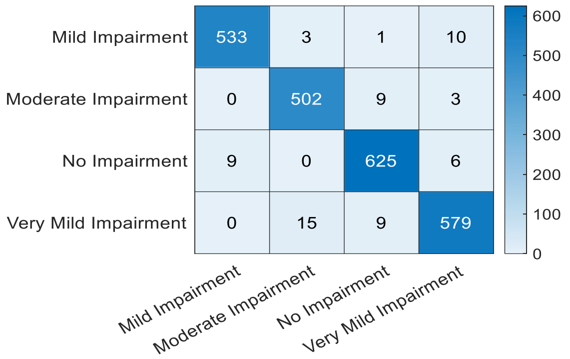


(a) PyTorch CNN



(a)Keras VGG16

[Fig.15: Confusion Matrix of DL]

Finally, the comparison of entire results is shown in table V taking 48 test images. Applying the maximum voting algorithm, the accuracy of detection is found to be 36/48 for the four categories of pictures and 41/48 for the two categories of images. The BoF provides an accuracy of 84.28% for individual classification cases. Two deep learning models, PyTorch CNN and Keras VGG, achieve accuracies of 95.7% and 97.1%, respectively, for classifying four types of images. Both DLs give better results compared to MLs and their combination, albeit at the expense of increased process time and space complexity.

V. CONCLUSION

For MRI images with subtle differences, the MLs reveal poor performance in classification, although the combined effort provides a moderate result. The signal processing approach of DWT is not applicable to extract features of such images, which are also offered in this paper. The BoF includes more than 100 features that can classify images with a maximum accuracy of 84.28% for test images. Two deep learning models, PyTorch CNN and Keras VGG, demonstrate accuracy above 95%. In the future, we will utilise Long Short-Term Memory (LSTM) with a variation of parameters, including some algorithmic modifications, to classify images. The combination of ML and DL will also be applied for performance comparison. All variants of CNN, such as ResNet, DenseNet, VGG-19, and YOLO, will also be applied for comparison.

Table- V: Comparison of Results for Test Images

Methods	% of Average Accuracy on Four Classes	% of Average Accuracy on Two Classes	Maximum Voting Combining Technique
DWT and Coherence	N/A	N/A	
SURF + MLR	29/48	35/48	
SURF + FCM	27/48	30/48	
SURF + FIS	27/48	33/48	
SURF + Corners Features FAST + Harris–Stephens+ minimum eigenvalue algorithm + MLR	31/48	34/48	
SURF + Corners Features FAST + Harris–Stephens+ minimum eigenvalue algorithm + FCM	33/48	33/48	
SURF + Corners Features FAST + Harris–Stephens+ minimum eigenvalue algorithm + FIS	32/48	36/48	Four classes: 36/48 Two classes: 41/48
SURF + Corners Features FAST + Harris–Stephens+ minimum eigenvalue algorithm + Linear SVM	33/48	38/38	
SURF + Corners Features FAST + Harris–Stephens+ minimum eigenvalue algorithm + Naïve Bayes	31/48	33/48	
BoF [15]	84.28%	100%	---
PyTorch CNN [16]	95.7%	100%	---
Keras VGG [17]	97.1%	100%	---

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- **Ethical Approval and Consent to Participate:** The

Retrieval Number: 100.1/ijeat.E467314050625
DOI: 10.35940/ijeat.E4673.15011025
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content of this article does not necessitate ethical approval or consent to participate with supporting documentation.

- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The Authorship of This Article Is Contributed Equally to All Participating Individuals.

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