ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25aug140

# Performance Evaluation of LBP, Mutual Information and CNN in Digital Diseases Image Detection

James Olujoba Adegboye[1]; Wasiu Oladimeji Ismaila[2]; Adeleye Samuel Falohun[3]; Abiodun Adebayo Owolabi[4]; Folasade Muibat Ismaila[5]

[1]Department of Computer Science, Federal Polytechnic, Ilaro, Ogun State, Nigeria.
[2]Department of Computer Science, Faculty of Computing and Informatics, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.
[3]Department of Computer Engineering, Faculty of Engineering and Technology, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[4]Department of Mathematics and Computing Sciences,Thomas Adewumi University, Oko-Irese, Kwara State, Nigeria.
[5]Department of Computer Science, University of Ilesha, Ilesha, Osun State, Nigeria.

Publication Date: 2025/09/04

**Abstract: Digital image processing is a field that employed computer algorithms to analyze digital images. Several images have been subjected to digital classifications like trauma-related, hypertensive, cancer, plant leaf diseases, breast cancer, etc. Feature extraction/selection is a pre-processing technique that removes redundant features from images. Several feature extraction/selection techniques, especially statistical and deep learning methods, have been employed by researchers but their performances have not dealt with adequately. This work focused on the performance comparison of three selected feature extraction and selection techniques viz; Local Binary Pattern, Mutual Information and Convolutional neural network in digital image processing. The datasets of MRI brain tumour images from the Kaggle website of 394 were pre-processed and also subjected to feature extraction and selection using the selected techniques. The extracted features were classified by Support Vector Machine and the outcome were evaluated by confusion matrix parameters.. The results showed the CNN-SVM based Image detection system at threshold of 0.85 produced Recall 84.8%, Specificity 95.9%, False Positive Rate 4.2%, Accuracy 92.9% and Precision 88.1%; the MI-SVM system produced Recall 70.5%, Specificity 92.0%, False Positive Rate 8.0%, Accuracy 86.3% and Precision 76.3%; while LBP-SVM system produced Recall 64.8%, Specificity 88.9%, False Positive Rate 11.1%, Accuracy 82.5% and Precision 68.0%.**

***Keywords:*** *Artificial Intelligence, Deep Learning, Local Binary Pattern, Mutual Information, Convolutional Neural Network, Digital Image Processing.*

**How to Cite:** James Olujoba Adegboye; Wasiu Oladimeji Ismaila; Adeleye Samuel Falohun; Abiodun Adebayo Owolabi; Folasade Muibat Ismaila (2025) Performance Evaluation of LBP, Mutual Information and CNN in Digital Diseases Image Detection. *International Journal of Innovative Science and Research Technology,* 10(8), 2193-2202. https://doi.org/10.38124/ijisrt/25aug140

## I. INTRODUCTION

In Artificial Intelligence realm, Digital Image Processing is an area that explores the use of computer algorithms or techniques to analyze digital images. Several image diseases related datasets have been subjected to digital image classifications like plant diseases data, trauma-related data [23]; hypertensive data [36]; cancer data [35]; [2] breast cancer, facial images [16] etc. Developing Digital image processing architecture involves four stages viz; image accumulation, pre-processing, feature extraction/selection and matching/classification. [26], [4],[27].

Feature extraction in machine learning is a critical process that transforms acquired mages into a set of meaningful and informative data while reducing redundancy, noise, and complexity. The primary goal is to simplify the data representation, making it more suitable for machine learning models to process and analyze effectively. Several feature extraction techniques have been employed in the

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25aug140

literature viz; principal component analysis (PCA) [9]; Linear Discriminate Analysis [4]; Independent Component Analysis (ICA) [ 24 ], Gabor filters [17]; Local Binary Pattern (LBP) and its variants [43].

However, feature selection is relatively similar to feature extraction, which is a pre-processing scheme used to remove unnecessary attributes from digital images. Due to data development which causes increment in dimensions-cum-computational costs are overcome by feature selection [28][34]. For instance, [3] employed particle swarm optimization; [1] used Ant Colony Optimization [21,27] employed gravitational search algorithm, deep learning by [22],[28],[29] etc. Deep neural network is one of the machine learning techniques that uses artificial neural networks (ANNs) to perform complex computations on large datasets. These algorithms are used in various industries such as healthcare, eCommerce, entertainment, and advertisement. Convolution Neural Network, Recurrent Neural Network, Mutual Information Model, Self-organising map, Generative Adversarial Network, Classical Neural Network, are some of the deep learning techniques [37]. Over the years there have been different researches to compare the performances of these feature extraction or selection techniques for optimum results which have brought relatively fair results. Thus, this paper extends the research by comparing the performances of Local Binary Pattern, Mutual Information model and Convolution Neural network in image processing system. Local Binary Pattern (LBP) is invented as local descriptor for micro-structures of digital images. LBP is used to explain the texture and shape of a digital image which is done by patitioning an image into several small regions from which the features are extracted [5],[33]. LBP has been employed by [25,43]. Mutual information (MI) is a powerful scheme for feature selection to identify the most relevant features. MI is used in filter feature selection as a measure of the dependency between a set of features selected and the classification prototypes. The final objective of feature selection is to minimize the classification error. Recently, researchers have used MI, which can be considered as higher order statistics [5], to identify the salient features [14,10,8], [7]. The main advantages of MI are the robustness to noise and data transformation. [13], [45].

Convolution Neural Network (CNN) is one of the most successful and broadly used architectures in deep learning. It is a feed-forward multilayer neural network has three layers viz; convolution layers, non- linear layers and pooling layers. The main advantage of CNN is the weight sharing mechanism through the use of the sliding kernel, which goes through the images, and aggregates the local information to extract the features. CNNs can easily learn features from labeled data and their implementations are easy to build. They also have great generalisation abilities [15,6,18,19,20,30]. The remaining part of this work is organized as follows: related work is presented in section II; Section III presents the relevant materials and methodology; Implementation of the developed System is in section IV; while discussion of results and comparison of techniques used are in Section V; and the Section VI concluded the work.

## II. RELATED WORK

[38] researchers in 2016 presented a crop diseases recognition model based on deep convolution networks for plant image classification.. With the ability to identify crops from their surroundings, the built model can recognize thirteen types of plant illnesses from healthy leaves. A deep learning framework (Caffe) was employed to perform the training and testing. The experimentation of the developed scheme showed that the results achieved precision of 96.3% on average. In 2020, the authors in [40] developed a deep learning model to improve accuracy of reported cases and to precisely predict the disease from chest X-ray scans. The model relied on Convolution neural networks (CNNs) to detect structural abnormalities and disease categorization that were keys to uncovering hidden patterns. The results gotten offered a very high accuracy of 96.3%.

The researchers in [25] investigates discrimination capabilities in the texture of images to differentiate between pathological and healthy images. Hence, the performance of Local Binary Patterns (LBP), LBP filtering and local phase quantization as a texture descriptor for retinal images were compared. The goal is to distinguish between diabetic retinopathy (DR), age related macular degeneration and normal fundus images analyzing the texture of the retina background and avoiding a previous lesion segmentation stage. Five experiments were designed and validated with the proposed procedure obtaining promising results. For each experiment, several classifiers were tested. An average sensitivity and specificity higher than 0.86 in all the cases and almost of 1 and 0.99, respectively, for AMD detection were achieved.

In 2022, the authors in [30] detected the presence of diabetic retinopathy in fundus images and grade the disease severity without lesion segmentation. A series of preprocessing steps were used to produce fundus images that are in a standard state of brightness. Uniform LBPs was used to extract features from acquired data. A proposed CNN-SVM model were used to classify retinal fundus images. The result showed that the developed system produced average F1-score of 0.974 and an average accuracy of 96.99% on the databases..

In 2023, [31] authors proposed a lightweight CNN named ChestX-ray6 that automatically detects pneumonia, COVID19, cardiomegaly, lung opacity, and pleural from digital chest x-ray images. In the study, multiple databases were combined, containing 9,514 chest x-ray images of normal and other five diseases. The pre-trained ChestX-ray6 model has achieved an accuracy and recall of 97.94% and 98% for binary classification, which outweighs the state-of-the-art (SOTA) models. [4] researchers in 2024 presented a comparative performance analysis of selected feature extraction techniques in human face images. Ninety face images were acquired pre-processed after which they were subjected to selected feature extraction techniques (LBP, PCA, Gabor filter and LDA). The extracted features were then classified using Back-propagation neural network. The results of recognition accuracy produced by Gabor filter, PCA, LDA and LBP at 0.76 threshold are 76.7%, 72.2%. 78.9% and 85.6%. [7] authors developed a sophisticated computer model using a deep CNN to accurately identify pneumonia in chest X-rays images. The model was trained on a vast collection of X-ray images, learning to distinguish between healthy and pneumonia-affected lungs. The results were impressive, on the test dataset, accuracy of 95.19%.

## III. MATERIALS AND METHODS

This research employed five stages which include data acquisition, data pre-processing stage, feature extraction/selection, data classification and evaluation stage. The flowchart is shown in figure 1.

### *A. Data Acquisition*

Datasets of MRI brain tumour images from the Kaggle website were acquired. The datasets comprise of 394 MR images. The data consists of gliomas, meningiomas and pituitaries.

### *B. Pre-Processing Stage*

The acquired datasets were subjected to pre-processing including images cropping /re-sizing to uniform pixel dimensions, contrast adjustment and conversion to grayscale. Therefore, noise filtering was applied. Filtering in image processing serves the primary purpose of achieving interpolation, noise reduction, and resampling. In this study, a combination of mean and median filters with different pixel values was employed to remove noise from MRI images.

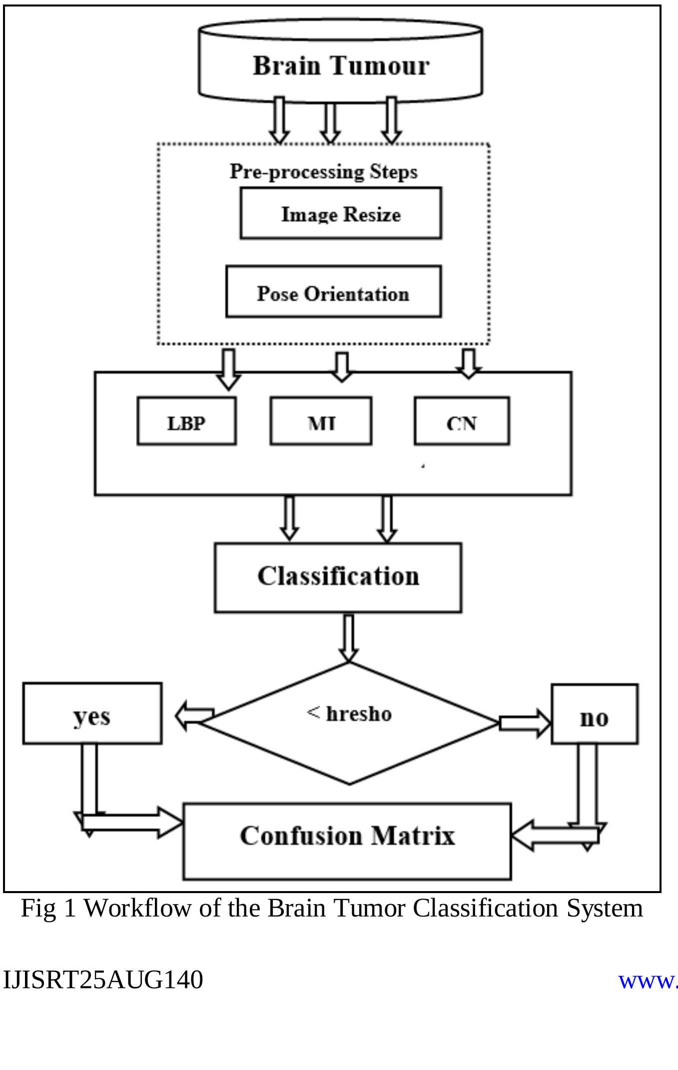


Fig 1 Workflow of the Brain Tumor Classification System

### *C. Feature Extraction/Selection*

The section describe the feature extraction techniques used for the images detection. These techniques are LBP, MI and CNN.

➢ *LBP*

LBP is relatively new approach introduced in 1996 by [32]. The LBP operator labels the pixels of an image by thresholding the 3 × 3-neighborhood of each pixel with the center value and considering the result as a binary string or a decimal number.With LBP it is possible to describe the texture and shape of a digital image. [11]. The LBP algorithm is shown in Algorithm 1.

- *Algorithm 1: The LBP Algorithm [32]*

✓ Step 1: Set $g_c$ which corresponds to the gray value of the center pixel

✓ Step 2: Set $g_p$ as the gray values of the "n" neighbor pixels

✓ Step 3: Set $M = \begin{Bmatrix} 1, & \text{if} g_c \geq 0 \\ 0, & \text{if} g_c < 0 \end{Bmatrix}$

✓ Step 4: Compute LBP features as described thus;

$$LBP_{p,r}(x_c, y_c) = \sum_{p=0}^{n-1} M(g_p - g_c) * 2^p$$

Where $x_c$ and $y_c$ represent te horizontal and vertical components of the image; $Mg_p$ and $Mg_c$ are neighborhood patterns, P represents the bit binary number resulting in $2^p$ distinct values for the LBP code.

✓ Step 5: Output selected LBP features

➢ *MI*

In accordance with Shannon's information theory [5], the uncertainty of a random variable *C* can be measured by the entropy *H(C)*. For two variables *X* and *C*, the conditional entropy *H(C/X)* measures the uncertainty about *C* when *X* is known, and the MI *I(X;C)* measures the certainty about that is resolved by *X*. Apparently, the relation of *H(C), H(C/X)* and *I(X;C)* is *H(C), = H(C/X) + I(X;C)* equivalently.

$$I(X;C) = H(C), - H(C/X) \quad (1)$$

The objective of training classification model is to minimize the uncertainty about predictions on class labels *C* for the known observations *X* . Thus, training a classifier is to increase the MI, *I(X;C)* as much as possible. Zero value of *I(X;C)* means that the information contained in the observations *(X)* is not useful for determining their classes *(C)*. The goal of a feature selection process for classification is naturally to achieve the higher values of *I(X;C)* with the smallest possible size of feature subsets. With the entropy defined by Shannon, the prior entropy of is expressed as.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25aug140

$$H_s(C) = \sum_{c\in C} P(c)\, log\, P(C) \quad (2)$$

Where P(c) represents the probability of *C*. The conditional entropy *H(C\X) is*

$$H_s(C) = -\int_x P(x)\, (\textstyle\sum_{c\in C} P(c/x)\, log\, P(C/x)\, dx) \quad (3)$$

The MI between *X* and *C is*

$$I_s(X;C) = \sum_{c\in C}\int_x P(c,x)\, log \frac{P(c,x)}{P(c)P(x)}\, dx \quad (4)$$

The forward feature selection process in terms of MI is formulated in Algorithm 2.

- *Algorithm 2: MI Algorithm [10]*

- ✓ (Initialization) Set *F* to the Initial Feature Set, *S* to the empty set;
- ✓ $\forall f_i \in F$ compute I($C_i$,$f_i$ )
- ✓ Find the feature $f_k$ that maximizes $I(C_i, f_i)$, put $f_k$ into *S* and delete it from F;
- ✓ (Greedy searching) repeat until the stopping criterion is met

- Calculate $I(C;S + f_i)\ V_{fi} \in F$ ;
- Choose the feature $f_k$ ($f_k \in$ F) that maximizes $I(C;f_i + S)$ put $f_k$ into *S* and delete it from *F*

- ✓ Output the features set *S*

➢ *CNN*

A CNN has three layers: a convolutional layer, a pooling layer, and a fully connected layer as shown in Fig 2.

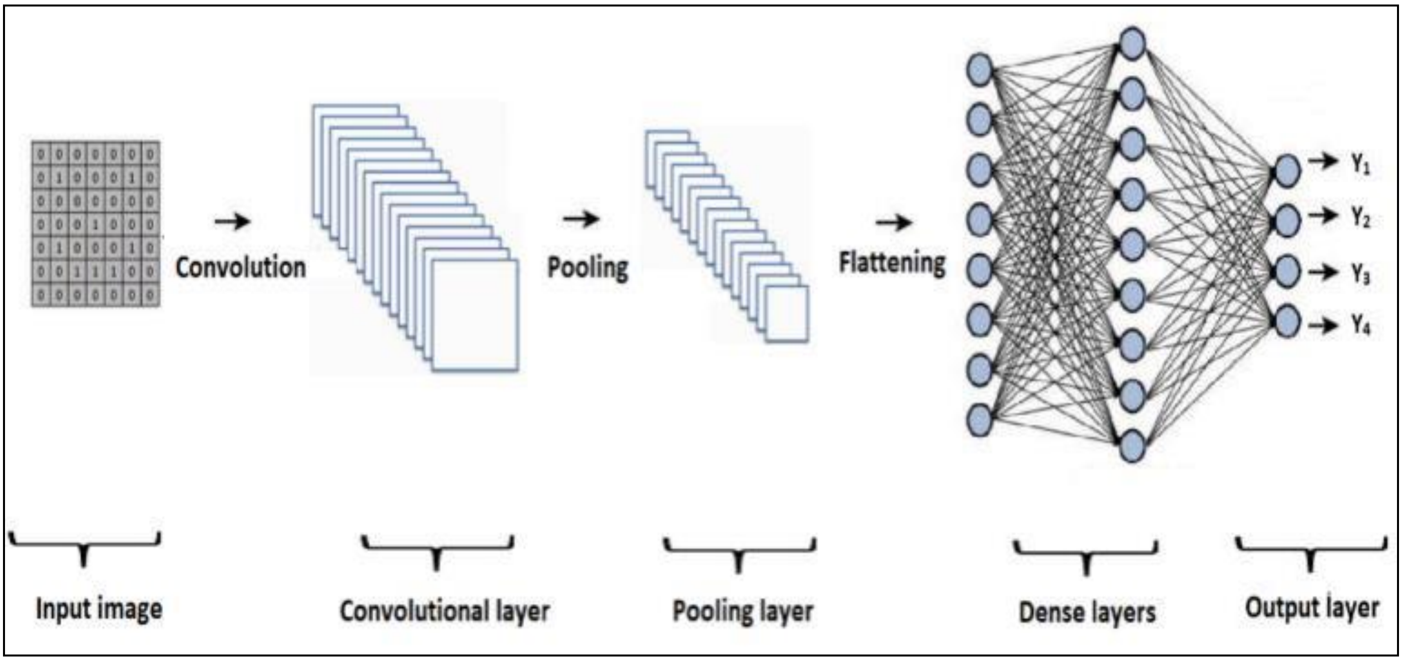


Fig 2 CNN Architecture [7]

Convolutional layer produces an activation map by scanning the pictures several pixels at a time using a filter. Pooling Layer reduces the amount of data created by the convolutional layer so that it is stored more efficiently. While in fully connected input layer: the preceding layers' output is "flattened" and turned into a single vector which is used as an input for the next stage. The first fully connected layer – adds weights to the inputs from the feature analysis to anticipate the proper label. Fully connected output layer – offers the probability for each label in the end [7,31]. The pseudocode of CNN is in algorithm 3.

- *Algorithm 3: Pseudocode of CNN [7]*

Parameters: input $x$ (512,1), output $y_t$ (512,5)
**For** each epoch **do:**
 # CNN Feature Extraction
  **For** each convolutional layer **do:**
   **for** each sample in $X$ **do:**
    Calculate $a_{ij}^m$ from $X$ by the convolution layer process
   **End for**
  #Dimension of $a$ is (512 – *KernelSize* + 1, *FilterSize*)
   **If** $a_{ij}^m$ *length* < 512 **do:**
    Apply zero padding to $a_{ij}^m$
    #Dimension of $a$ is (512, *FilterSize*)
   **End if**
  **End for**

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25aug140

```
    For each sample in a do:
        Calculate Forward Pass of a
        Calculate Backward Pass of a
    # Dimension of the output a is (512,2*NeuronSize)
        Calculate y_t
    End for
End for
```

*D. Classification Stage*

Classification is the process of categorizing a given set of data produced by feature extraction/selection into classes. Once features have been extracted/selected from the acquired images, then classification stage is next. Support Vector Machine (SVM) is employed for this purpose. More information can be found in [42, 44].

*E. Performance Metrics*

The performance of the techniques understudy was evaluated based on recognition accuracy (acc), specificity (spec), False Positive Rate (FPR), precision (prec), and Recall. The values of the performance measures were determined using a confusion matrix. As defined in Equations 5 to 9. It comprises "True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN)."

$$\text{False Positive Rate (FPR)} = \frac{FP}{TN+FP} \quad (5)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (6)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (9)$$

## IV. RESULTS

The To evaluate the selected techniques performance, we used the following metrics: False Positive Rate (FPR), Accuracy (ACC), Sensitivity (SEN), Specificity (SPEC), and recognition time. These metrics were analyzed for different average threshold values (0.3, 0.55, and 0.85).

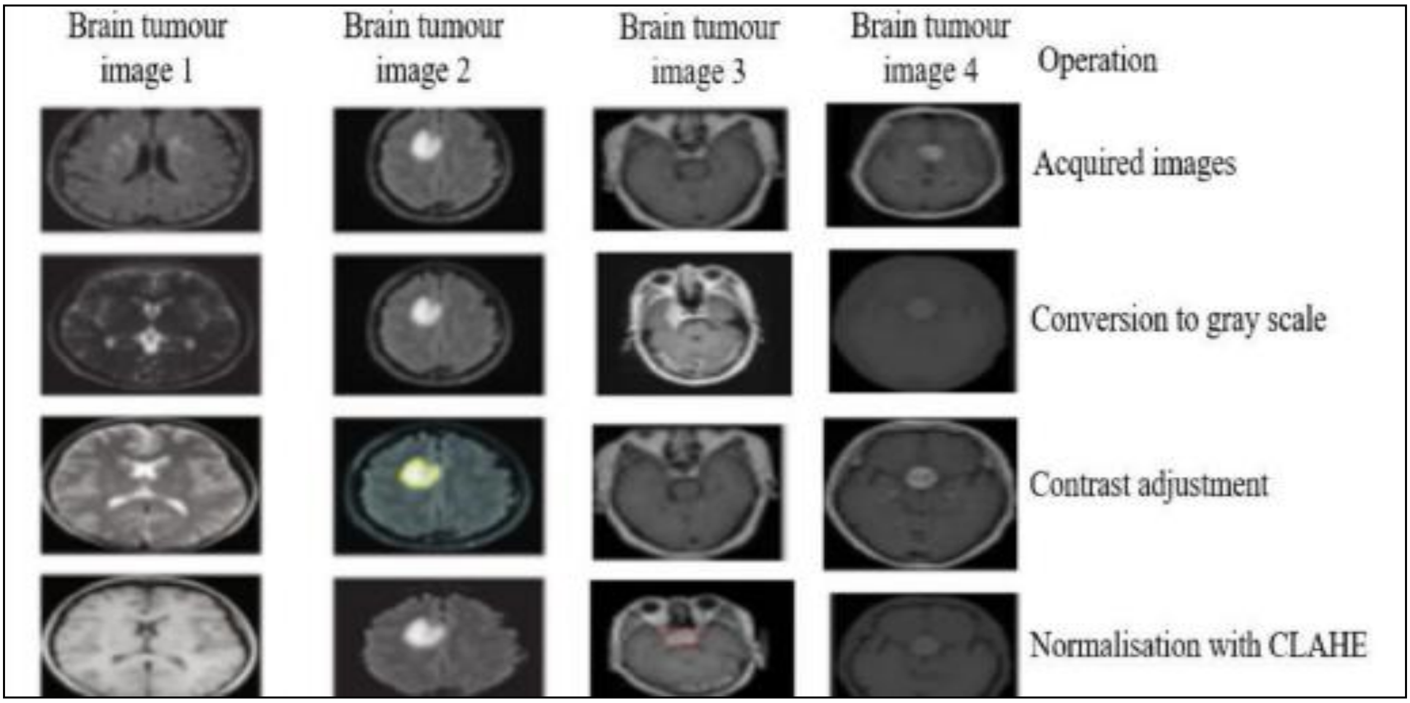


Fig 3 Results of the Preprocessing Stages.

Table 1 LBP-SVM Based Tumour Detection System

| THRESH | RECALL | SPEC | FPR | ACC | PREC |
|---|---|---|---|---|---|
| 0.3 | 52.4 | 76.5 | 23.5 | 70.1 | 44.7 |
| 0.55 | 56.2 | 83.4 | 16.6 | 76.1 | 55.1 |
| 0.85 | 64.8 | 88.9 | 11.1 | 82.5 | 68.0 |

From table 1, the developed LBP-SVM based Image detection system at threshold of 0.3 produced Recall 52.4%, Spec 76.5%, FPR 23.5%, ACC 70.1% and PREC 44.7%. At threshold 0.55 the system produced Recall 56.2%, Spec 83.4%, FPR 16.6%, ACC 76.1% and PREC 55.1%. While at threshold 0.85 the system produced Recall 64.8%, Spec 88.9%, FPR 11.1%, ACC 82.5% and PREC 68.0%.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25aug140

Table 2 MI-SVM Based Image Detection System

| THRESH | RECALL | SPEC | FPR | ACC | PREC |
|---|---|---|---|---|---|
| 0.3 | 55.2 | 79.2 | 20.8 | 72.8 | 49.2 |
| 0.55 | 61.9 | 85.1 | 14.9 | 78.9 | 60.2 |
| 0.85 | 70.5 | 92.0 | 8.0 | 86.3 | 76.3 |

From table 2, the developed MI-SVM based Image detection system at threshold of 0.3 produced Recall 55.2%, Spec 79.2%, FPR 20.8%, ACC 72.8% and PREC 49.2%. At threshold 0.55 the developed system produced Recall 51.9%, Spec 85.1%, FPR 14.9%, ACC 78.9% and PREC 60.2%. While at threshold 0.85 the system produced Recall 70.5%, Spec 92.0%, FPR 8.0%, ACC 86.3% and PREC 76.3%.

Table 3 CNN-SVM Based Image Detection System

| THRESH | RECALL | SPEC | FMR | ACC | PREC |
|---|---|---|---|---|---|
| 0.3 | 67.6 | 84.4 | 15.6 | 79.9 | 61.2 |
| 0.55 | 73.3 | 89.3 | 10.7 | 85.0 | 71.3 |
| 0.85 | 84.8 | 95.9 | 4.2 | 92.9 | 88.1 |

From table 3, the developed CNN-SVM based Image detection system at threshold of 0.3 produced Recall 67.6%, Spec 84.4%, FPR 15.6%, ACC 79.9% and PREC 61.2%. At threshold 0.55 the developed system produced Recall 73.3%, Spec 89.3%, FPR 10.7%, ACC 85.0% and PREC 71.3%. While at threshold 0.85 the system produced Recall 84.8%, Spec 95.9%, FPR 4.2%, ACC 92.9% and PREC 88.1%.

From tables 1, 2 and 3, at threshold 0.85, CNN-SVM based system produced the best results in terms of all the metrics employed while MI-SVM based system produced better results that LP_SVM based detection system. The graphs of the results generated by the three techniques are shown in figure 4,5,6,7 and 8.

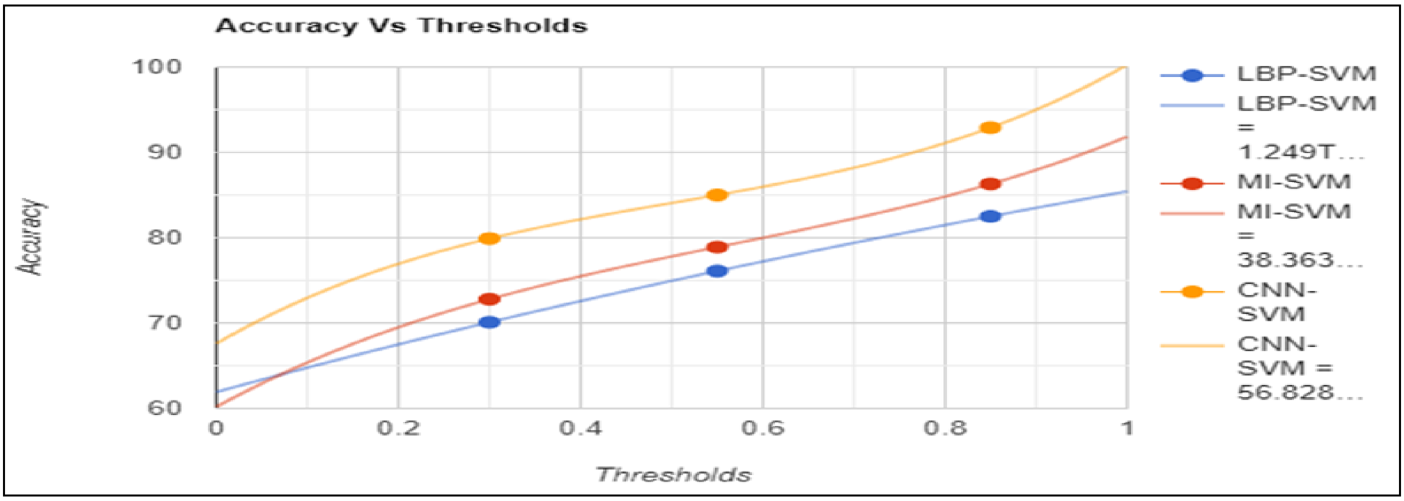


Fig 4 Graphs for Accuracy vs Threshold

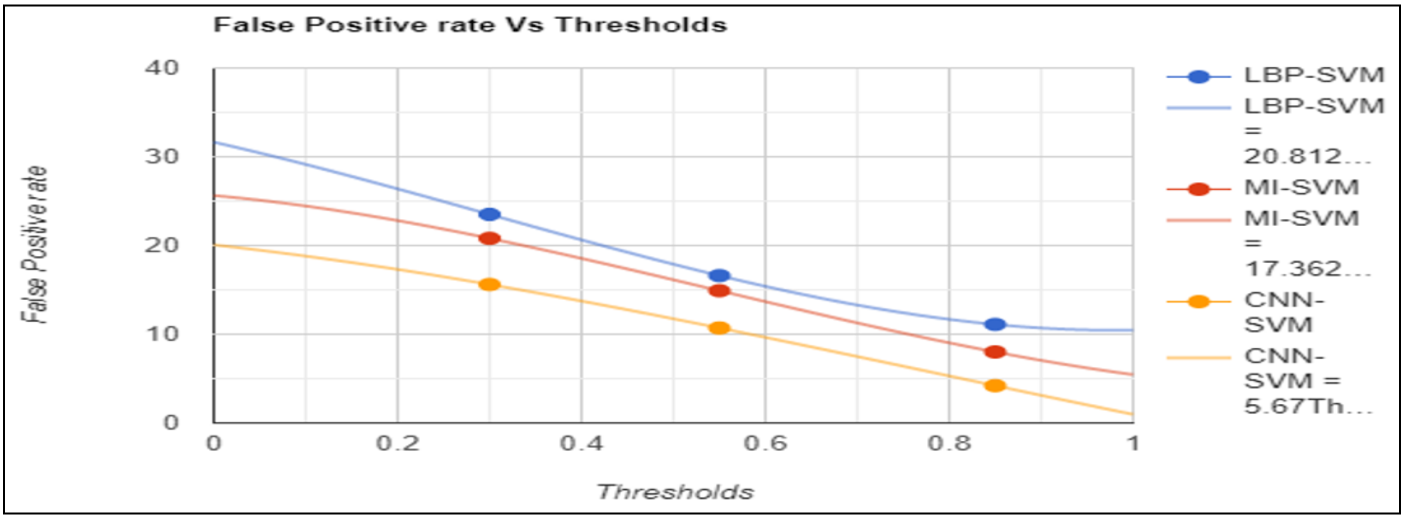


Fig 5 Graphs for FPR vs Threshold

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25aug140

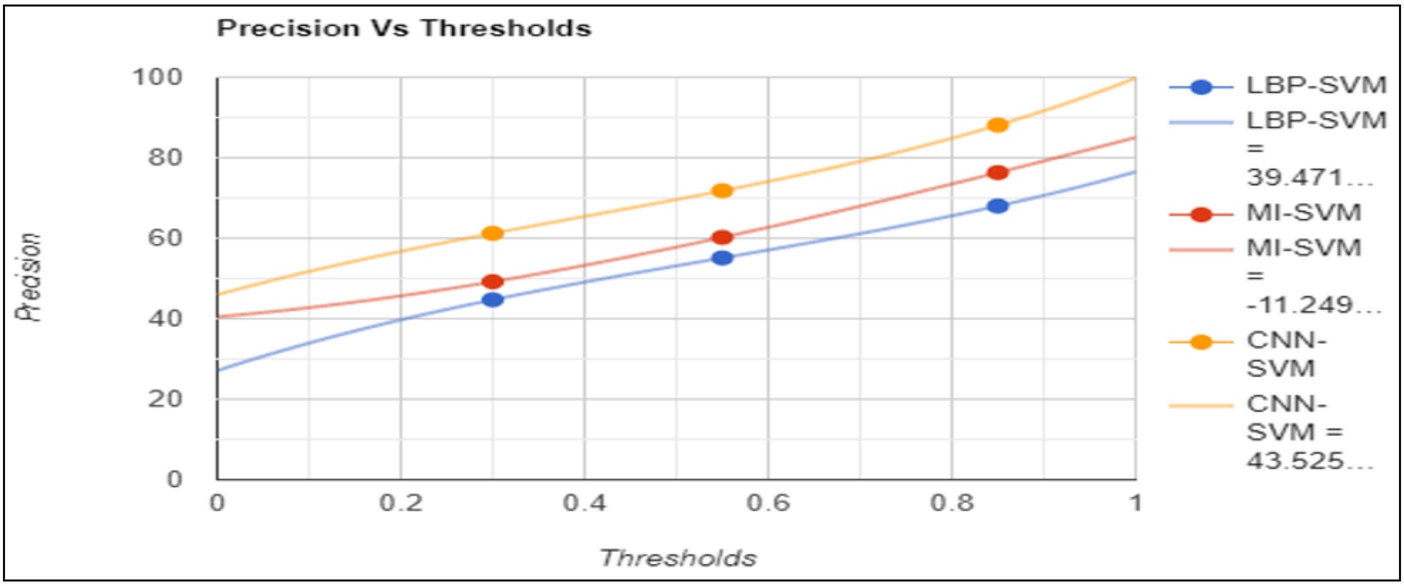

Fig 6 Graphs for Precision and Threshold

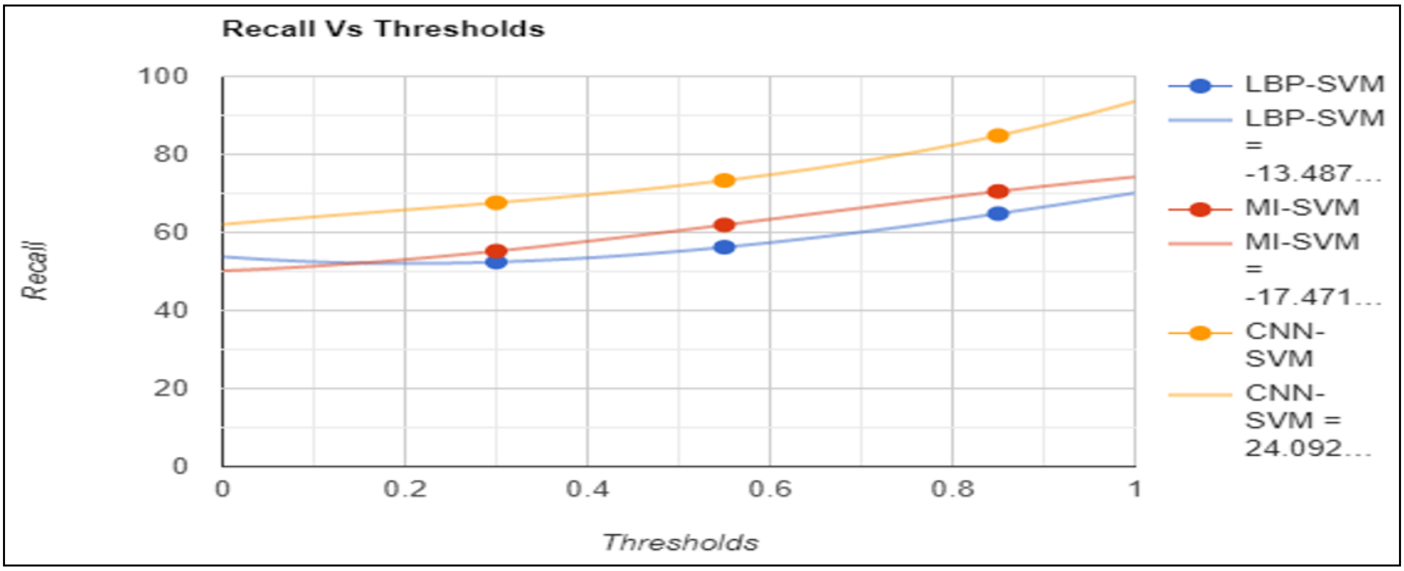

Fig 7 Graphs for Recall vs Threshold

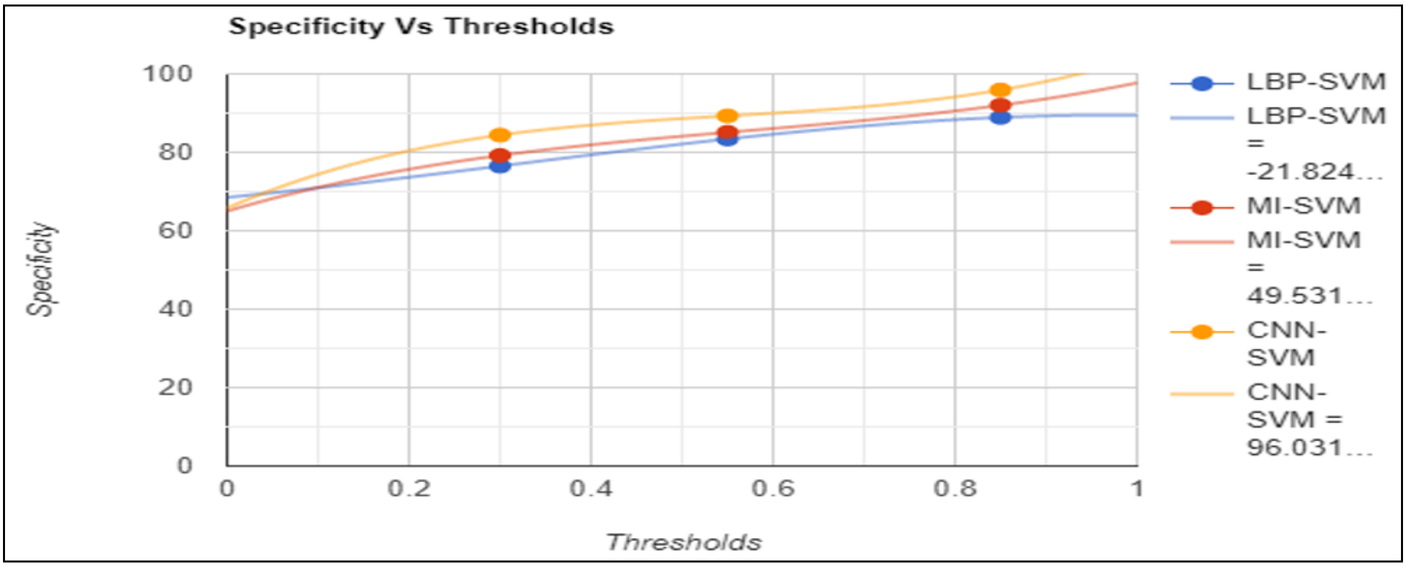

Fig 8 Graphs for Specificity and Threshold

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25aug140

## V. DISCUSSION

➢ *As Stated in Table 1, 2 and 3, it could be Deduced that:*

- In case of FPR , the results showed that CNN-SVM yielded a lesser FPR than MI-SVM and LBP-SVM. this implies that CNN-SVM is less prone to false positive error in than MI-SVM and LBP-SVM.
- In case of Recall, the results showed that CNN-SVM has higher recall than MI-SVM and LBP-SVM which implies that CNN-SVM has the ability to identify the presence of images (true positives) in the database.
- In case of Specificity: the results showed that CNN-SVM has higher specificity than MI-SVM and LBP-SVM, which implies that CNN-SVM has the ability to identify the absence of images (true negatives) in the database.;
- In case of Precision: the results showed that CNN-SVM produced hiher precision than MI-SVM and LBP-SVM, this implies that CNN-SVM has better positive predictive capability.
- In case of Accuracy, the results showed that CNN-SVM gave higher value than both MI-SVM and LBP-SVM. this implies that CNN-SVM has the ability to identify the presence and absence of images (true negatives and true positives) in the database.

## VI. CONCLUSIONS

This work was based on experimentation selected feature extraction and selection techniques viz LBP, and two deep learning techniques (MI and CNN) on digital diseases database. These techniques were selected based on their notable performances in image classification problems. The evaluation procedure employed four stages which are image acquisition, pre-processing, feature extraction/selection and data classification. The diseases datasets were first pre-processed and then subjected to selected feature extraction/selection techniques (LBP, MI and CNN). The extracted/selected features were then classified with SVM. The results of recognition accuracy produced by LBP, MI and CNN at 0.85 threshold are 82.5%, 86.3% and 92.9% respectively. Hence, it can be deduced that CNN performed the best than other two feature extraction/selection techniques. However, this work can be improved on by considering other notable feature extraction/selection techniques for evaluation and also possibly improve the efficiency of any of these techniques through cascade or optimization methods.

## REFERENCES


[1]. Abikoye,O. C., Komolafe R. G. and Aro T. O. (2019). Performance Evaluation of Feature Selection Algorithms On Skin Disease Prediction, FUW Trends in Science & Technology Journal, 4(2), 337 – 342

[2]. Ahn .M., Kim H. E., Shin M., and Sim S.-H. (2019). Crack and non crack classification from concrete surface images using machine learning. Structural Health Monitoring, 18(3), 725–738.

[3]. Arunkumar M. and Valarmathy S. (2013). Palmprint and Face Based Multimodal Recognition Using PSO Dependent Feature Level Fusion, Journal of Theoretical and Applied Information Technology, 57(3), 337-346.

[4]. Agboola F. F., Ismaila W. O., Omotosho I. O.; Falohun A.S., Ismaila F. M. (2024). Evaluation of Gabor Filter, GLCM, and DWT Performance in Brain Tumour Classification. Journal of Science Innovation & Technology Research (JSITR). 05 (9), 103-118. Nigeria.

[5]. Ahonen, T., Hadid, A., Pietikainen, M. (2004): Face recognition with local binary patterns. In Proceedings of the European Conference on Computer Vision, Prague, Czech, 469–481.

[6]. Alzubaidi, L., Zhang, J., Hamaidi, A.J., Al-Dujaili, A. Duan, Y., Al-shamma, O., SantaMaria, J., Fadhel, M. A., Al-Amidie, M. and Farhan, L. (2021). 'Review of deep learning: concepts, CNN architectures challenges, applications, future directions'. *(Springer International Publishing) doi:10.1186/s40537-021-00444-8.*

[7]. An, Q., Chen, W., Shao, W.A (2024) Deep Convolutional Neural Network for Pneumonia Detection in X-ray Images with Attention Ensemble. Diagnostics 2024, 14,390.

[8]. Al-ani A. and Deriche, M. (2001). “An optimal feature selection technique using the concept of mutual information,” in *Proc. 6th Int. Symp. Signal Processing and Its Applications (ISSPA)*, Kuala Lumpar, Malaysia, 2001, pp. 477–480.

[9]. Afolabi A. O. and Adagunodo R. (2012). Implementation of an Improved Facial Recognition The algorithm in a Web-based Learning System, International Journal of Engineering and Technology Vol. 2, No. 11, pp 1885-1892.

[10]. Battiti, R. (1994). “Using mutual information for selecting features in supervised neural net learning,” *IEEE Trans. Neural Netw.*, vol. 5, no. 4, 537–550, Jul. 1994.

[11]. Bereta, M., Pedrycz, W. and Reformat, M., 2013. Local descriptors and similarity measures for Frontal face recognition: A comparative analysis. *Journal of Visual Communication and Image Representation*, 24(8), 1213-1231

[12]. Bonev B., Escolano F., Cazorla M. (2008). Feature selection, mutual information, and the classification of high dimensional patterns, Pattern Anal Applic., 11,:309–319.

[13]. Bonnlander B. V. and Weigend, A. S. (1994). “Selecting input variables using mutual information and nonparametric density estimation,” in *Proc. Int. Symp. Artifificial Neural Network (ISANN),* Taiwan, 1994, 42–50.

[14]. Cover T. M. and Thomas, J. A. (1991). *Elements of Information Theory*. New York: Wiley, 1991.

[15]. Darwish, A., Ezzat, D. and Hassanien, A. E. (2020). An optimized model based on convolutional neural networks and orthogonal learning particle swarm optimization algorithm for plant diseasesdiagnosis.

*Swarm and Evolutionary Computation*, 52, 100616. doi: htpps;//doi.org/ 10.1016/j.swevo.2019.100616.
[16]. Deepesh R. (2011). A Realtime Face Recognition system using PCA and various Distance Classifiers, Computer vision and processing. 5(3), 15-22.
[17]. Deshpande S., and Apte S. D. (2014). Facial Emotion Recognition using Gabor Features, International Journal of Electronics Communicationand Computer Engineering, Volume 5, Issue July, Technovision-2014, ISSN 2249–071X.
[18]. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M. and Thrun, S. (2017) “Dermatologist-level classification of skin cancer with deep neural networks,” *Nature*, 542 (7639): 115-118.
[19]. Ezzat, D., Hassanien, A.E. and Aboul-Ella, H. (2020). An Optimised deep learning architecture for the diagnosis of COVID-19 disease based on gravitational search optimisation *Applied Soft Computing Journal, 98 (2021), 106742.*
[20]. Fan, J., Xu, W., Wu, Y., and Gong, Y. (2010). Human tracking using convolutional neural networks. *IEEE Transactions on Neural networks*, 21(10). 1610-1623.
[21]. Fatemeh, S. F. Mansour S. and Ali F. (2013). Facial Emotion Recognition Using Gravitational Search Algorithm for Colored Images, AISP 2013, CCIS 427, 32–40.
[22]. Guo, Y., Liu, Y., Oerlemans, A., Lao, S., Wu, S. and Lew, M. S. (2016). "Deep Learning for Visual Understanding. A review", *Neurocomp*., 187, 27-48.
[23]. Hassanipour S., Ghaem H., Arab-Zozani M., Seif, M., Fararouei, M., Abdzadeh, E., Paydar, S.(2019). Comparison of artificial neural network and logistic regression models for prediction of outcomes in trauma patients: A systematic review and meta-analysis. Injury, 50(2), 244–250.
[24]. Ismaila W. O., Adetunji A. B., Falohun A. S. and Iwashokun G. B. (2012). A Study of Features Extraction Algorithms for Human FaceRecognition. Transnational Journal of Science and Technology, 2(6), 14-22
[25]. Indraja K., Krishna N. Chaitanya (2018). Blood Vessel Extraction and Retinal Disease Detection Using Local Binary Patterns. International Journal of Advanced Technology and Innovative Research , vol. 10, Issue no. 08, 0981-0986.
[26]. Ismaila Folasade M., Afolabi Adeolu O, Alo Oluwaseun O, Ismaila W. Oladimeji (2024).Performance Evaluation of Selected Feature Extraction Techniques in Digital Face Image Processing. International Journal of Innovative Science and Research Technology, 9(1), 2292-2300.
[27]. Ismaila Folasade M., Afolabi Adeolu O, Alo Oluwaseun O, Ismaila W. Oladimeji, Funmilayo A.Ajala (2024). Comparative Analysis of Selected Evolutionary Algorithms as Feature Selectors in Digital Face Image Processing. International Journal of Recent Research in Mathematics, Computer Science and Information Technology, 10(2), 53-62.
[28]. Minace, A., Rivera, P. and Johnson, R. (2019). “Deep learning for biometric recognition,” Applied Computing Research, 56(2) 120-140.
[29]. Minace, S., Boykov, D. and Zhang, Y. (2019). “Deep learning in biometrics,” *IEEE Access,* 7(4): 102-120.
[30]. Mohamed A. Berbar (2022). Features extraction using encoded local binary pattern for detection and grading diabetic retinopathy. Health Information Science and Systems 10:14.
[31]. Nahiduzzaman, M., Islam, M. R., and Hassan, R. (2023). ChestX-Ray6: Prediction of multiple diseases including COVID-19 from chest X-ray images using Convolutional neural network. *Expert Systems with Applications*, 211, 118576
[32]. Ojala T., Pietikainen M. and Harwood D., (1996). “A comparative study of texture measures with classification based on feature distributions” *Pattern Recognition*. 29, 1996.
[33]. Ojala, T., Pietikainen, M., Maenpaa, M. (2002) Multi-resolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence 24(7), 971–987.
[34]. Prasetiyowati,M. I., Maulidevi N. U. and Surendro K. (2021). Determining threshold value on information gain feature selection to increase speed and prediction accuracy of random forest, *Journal of Big Data (2021)* 8:84.
[35]. Ruchi C. (2015). Facial Expression Recognition Using Facial Movement Features, Computer Science & Engineering, India, vol. 4 Issue 4, 2318 – 2324.
[36]. Sarangi, S, Sahidullah, M,; Saha, G. (2020). "Optimization of data-driven filterbank for automatic speaker verification". Digital Signal Processing. 104.
[37]. Subramanian, N., Elharrouss, O., Al-Maadeed, S., & Chowdhury, M. (2022). A review of deep learning-based detection methods for COVID-19. Computers in Biology and Medicine, 105233.
[38]. Sladojevic, S. and others (2016). ”Deep neural networks based recognition of plant diseases by leaf image classification.” Computational intelligence and neuroscience 2016.
[39]. Tommy W. S. Chow, *S*and D. Huang (2005). Estimating Optimal Feature Subsets Using Efficient Estimation of High-Dimensional Mutual Information, IEEE Transactions on Neural Networks, vol. 16,
[40]. Vaid, S., Kalantar, R., and Bhandari, M. (2020). Deep learning COVID-19 detection bias: accuracy through artificial intelligence. *International Orthopaedics*, 44, 1539-1542.
[41]. Wang D, Mo J, Zhou G, Xu L, Liu Y (2020) An efficient mixture of deep and machine learning models for COVID-19 diagnosis in chest X-ray images. *PLoS ONE*15(11): 1-15.
[42]. Xiao Z., Zheng O. and Yonggiang O. (2018). *CSAI ’18 Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence*, 263-267.
[43]. Sristi K., Pallabi D., Sharanya P., Disha D., Bikram K., Arti K., Ausaf M., Moloy D. (2023). LBP Feature Extraction for Early Detection of Diabetic Eye Diseases. International Journal for Research in Applied Science & Engineeringb Technology (IJRASET)

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25aug140

[44]. Vapnik V., and Cortes C.(1995). Support-Vector Machine, Machine Learning, 20, 273-297.
[45]. Yang H. H. and Moody,J. (1999). "Feature selection based on joint mutual information," in *Proc. Int. ICSC Symp. Advances in Intelligent Data Analysis*, Rochester, New York, 1999, 342–349.