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An Optimal Texture Pattern Model Of Face Recognition Using MMOO-CDNN

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ABSTRACT

Different forms of data prediction models are used in image processing to recognize the type of data and predict its class label. Among these models, the texture pattern-based occluded face recognition method stands out as it improves the prediction performance compared to other feature representation methods. However, this method also increases the size of features for the images, resulting in the need for big data processing. The proposed model focuses on recognizing the form of occlusion type and identify the person by the occluded face image. To conduct this work, we propose the texture pattern for extracting image using the Flit Synchronized Texture Pattern (FSTP), which implements a distribution function to represent the image texture pattern based on the intensity of the image matrix. Furthermore, the Multi-Model Osprey Optimization (MMOO) method is employed to optimize the texture feature for the big data of image texture feature matrix. This ensures that the image classification model is efficient and effective in handling large amounts of data. To classify the face and to identify the person from occluded face images, Correlative Directional Neural Network model is utilized and the performance of the proposed model is validated using Real World Occluded Faces (ROF) dataset consisting of 5559 images of 180 persons. The results and comparative analysis demonstrate that the proposed model outperforms traditional classification and prediction methods in terms of performance enhancement.

Keywords—Face Recognition, Person Identification, Texture Feature Model, Image Classification, Big Data Analysis, Flit Synchronized Texture Pattern (FSTP), Multi-Model Osprey Optimization (MMOO), Correlative Directional Neural Network (CDNN).

I. INTRODUCTION

The image classification and prediction model includes a unique structure for data layout and image feature validation. In doing so, the prediction system ascertains the classes of images by utilizing the training model and the attributes of the image. A variety of technologies are used to compare the image attributes in order to illustrate the classification of different image types for the relevant application. A more reliable method of classifying visual data and facilitating prediction is artificial intelligence (AI), a relatively new technological advancement. As a result, a relatively new technological advancement. As a result, the pattern of occluded face matching coordinate points can be predicted using fewer data. Because there is insufficient information in the feature, there is a pattern mismatch in this instance, which lowers prediction accuracy. To increase performance, this has to improve the directionality of the pattern and be based on the training model. In order to estimate edge details and categories of occluded faces, this can be accomplished by validating picture characteristics at several critical forms of face texture. For this type of picture classification, the texture pattern-based image representation contributes to a higher classification accuracy when compared to other feature extraction techniques. In the convolution techniques the texture of an image is determine and then extracts its texture. To process these two methods are utilized to extract the features: Gabor convolution-based image texture prediction and Discrete Wavelet Transformation (DWT). Considering that some applications—such as the one for facial image prediction and others for object recognition—use binary patterns—such as Local Binary Pattern (LBP), Local Tetra Pattern (LTrP), Local Ternary Pattern (LTP), etc.—for the image matrix. All of them aim to recognize the texture of the image and draw attention to boundary differences in the picture matrix.

From the image feature extraction model, the attributes are gathered in a vector format produced, which is then used to represent the image's qualities as well as other pixel-related feature points. This indicates that selecting a classification is still another essential component for improving the accuracy of predictions regarding the types of images. Data as a form of image in binary and multi-class forms can be classified using machine learning techniques such as Support Vector Machine (SVM), Fuzzy Classification Model, and others. The Correlational Directional Neural Network approach is the most sensitive of these and improves the classification performance of the data learning model. When integrated with different domains of the image classification model, this yielded better results than other traditional classification models. To improve prediction accuracy, Relative Directional Neural Network and visual texture extraction are collaborated.
As a result of the numerous problems with texture classification in face pattern, including excessively smoothed pixels, improper similarity estimation, inability to detect similarities, etc., the proposed model addresses these problems by implementing a multi-directional visual pattern representation that makes neighboring pixels easily identifiable. This can be done by using the Flit Synchronized Texture Pattern (FSTP) feature extraction method. This was separated into block divisions in order to determine the relevant pixels between the borders and center of the FSTP. Subsequently, the magnitude of that cell was used to approximate its weight values. The visual matrix adheres to these throughout. This was then set up as the output matrix to show the visual pattern. This made it possible to estimate the pattern's histogram and extract the image's feature vector.
Using the pattern extraction technique of FSTP, the primary goal of this paper work is
1. To improve the face pattern based occluded person Identification classification model.
2. Utilizing the Multi-Model Osprey Optimization (MMOO) technique to handle and optimize the large set of face image data.
3. By applying a CGF filter, the impulse noise is reduced.
4. To use an enhanced pattern extraction method to cluster and analyze the filtered image.
5. Utilizing several texture blocks and edge prediction-based feature extraction techniques, to extract probabilistic and textural pattern characteristics.
6. To use boundary mapped Correlative Directional Neural Network based classifier with texture to classify and recognize the person ID from occluded face.
The following subsections can be used to arrange the overall details of the paperwork. Section II provides an overview of the current image texture pattern extraction and classification models. In section III, the suggested method and its phases are explained together with the equation model for the extraction of texture from images and the classification model. The performance results of the suggested method with the comparative statement are covered in Section IV. The results are shown graphically and, in a table, using statistical parameters. In Section V, the conclusion and future scope of this work is addressed.

II. RELATED WORK

In order to identify person using occluded faces, this survey determines the various texture pattern models and the image classification technique. Additionally, this illustrates the benefits and drawbacks of the current prediction system model with its varied parameter representation and validation.
In that, the research [1] describes how the facial features based on the pattern recognition are extracted. This indicates the occluded objects blocked face as well. In order to validate the occluded face category based on Global-structure Pattern, this work determines the sequence representation and integrates the morphological function. Comparably, the paper [2] combined the prediction procedure of the occluded face of object in persons ID. In this case, the Bayesian classification approach predicts the range of occluded faces carried by arthropods. [3] developed the Maximum Likelihood model for the pattern to determine the genetic pattern of the occluded face for persons in an effort to further improve the prediction level of the occluded face categories. The features of the occluded face structure are verified and illustrated in [4] for the zoonotic parasite prediction. As a result, the survey of parasitic obstructed faces is now classified. In order to verify the occluded face in persons with occluded faces, [5] reported a survey of texture pattern type, which causes occlusion in the face. By employing the Sanger technique, the data are structured in this way: in the forward and reverse directions of the vector feature mode, represented in succession. This is an improvement to the data sequence model made by the automation system. A review of occluded face theileriosis based on important data attributes from the past, present, and future was reported in the publication [6]. In order to distinguish between the objects and the color pattern of the facial data, the publication [7] suggested a prediction of facial key points. To access the validation procedure in this, two form of texture pattern and the geometrical features are used. In a similar form of pattern modeling and the prediction system is depicted in the study [8]. Furthermore, examined in [9] are texture prediction and the optimal feature selection. This work pertains to occluded object investigation that is connected to facial features. The prediction and validation of occluded face species for occluded faces was examined in [10] using the intracellular mask matrix representation. Rather than relying on sequences that encode binary patterns, this was discovered using masking method and feature data. Optimal method of feature selection diversity and trends were used to predict in [11]. This is an illustration of the person's fine-scale variety in urban environments. In [12], the species diversity and genome of pathogenic protozoa are examined.
Analysis of the detection of occluded objects on faces was done in [13]. Here, the presence on the occluded face was used to assess the detection. In a similar manner, the fecal testing in [14] was conducted to check for

blocked facial features and the pattern prediction. The centralized authorization method of the European Union was used to examine the pattern extraction in [15] and [16]. This helped with the field research on vaccinations for persons. Alginate nanoparticles were used in [17] to quantify and improve the prediction quality of image pattern. In this case, the analysis and prediction of occluded face types are performed using images in the TEM format. The multi-objective [18] analysis of occluded face prediction includes this kind of identification. Stress-Related Herpesvirus Reactivation in Badgers predicted the kinds of Clostridium Proliferation [19]. The occluded face kinds are recognized and categorized according to the pattern structure. [20] describes how the data characteristics are analyzed for the multiple occluded face categories after processing the Differential prediction. A prediction and analysis of pattern extraction model was done in [21]. This study concentrated on face profiling, diagnostic real-time sequence of input, and occluded facial detection.

III. PROPOSED WORK

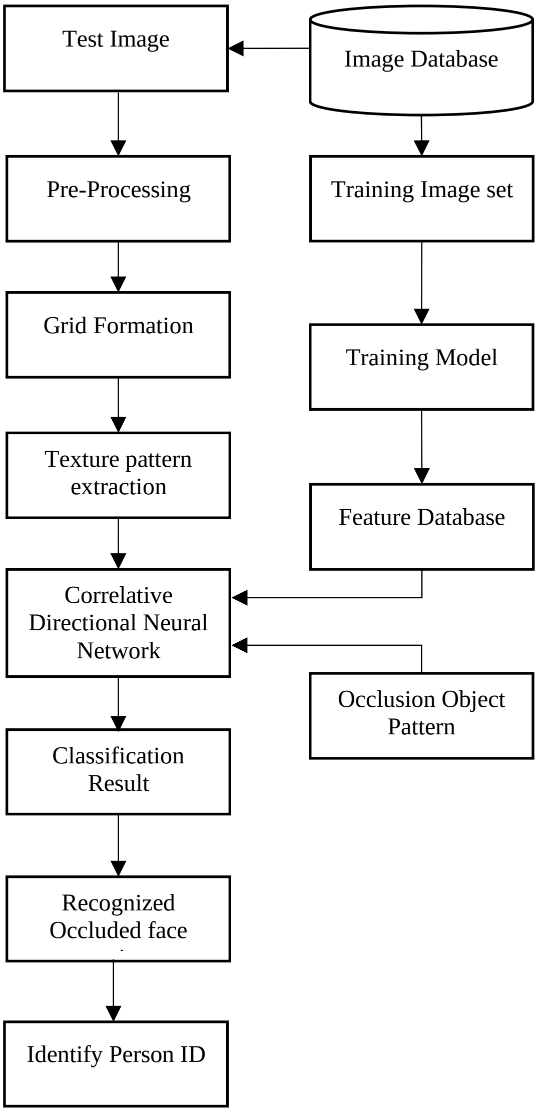

Figure 1 Overall flow diagram of proposed occluded face recognition model

The use of the multi-directional pixel representation approach for texture-based occluded face image classification is shown in this work. The Flit Synchronized Texture Pattern (FSTP) was used to calculate the difference in neighboring pixels using the distribution model. Here, the distribution is utilized to display the range of similarity for the border estimation of the image matrix. This improves the prediction level based on the intensity difference in the cell matrix. When a correlative direction neural network is integrated with the recommended texture pattern, the prediction performance is much improved with high sensitivity.

The following summarizes the primary goal of the suggested occluded face prediction based on the texture pattern:

1. The picture matrix's pixels are improved using the filtering method based on cellular automata.

2. The estimation of the surrounding difference to represent the border is improved by the distribution-based texture pattern extraction.
3. Using a high similarity value, this method of texture extraction calculates the depth information of the image intensity.
4. Using a high accuracy and precision rate, the Correlative Directional Neural Network classifies the feature matrix according to the provided training set.

Three subsections that make up the overall suggested model are as follows:

a) Image enhancement,
b) Texture Pattern Extraction,
c) Feature Optimization,
d) Feature Classifier.

A. Image Enhancement

During this pre-processing stage, the image was submitted to a filtering model, which boosts pixel intensity and smooths out the image [20]. The convolution for both the mask value and the image cell is carried out by the mask in the filtering model as it traverses the whole image matrix. This is the process of optimizing picture pixels. The method of applying filtering and enhancing functions to an image through the cell creation of an image matrix is referred to as "cellular automata" to implement the CGF filtering method. Together with the other pixel characteristics obtained from this filtering model result, the object borders are enhanced by the depth information of the picture boundaries. The figure 2 shows the sample result of pre-processing in three different image classes for the same person.

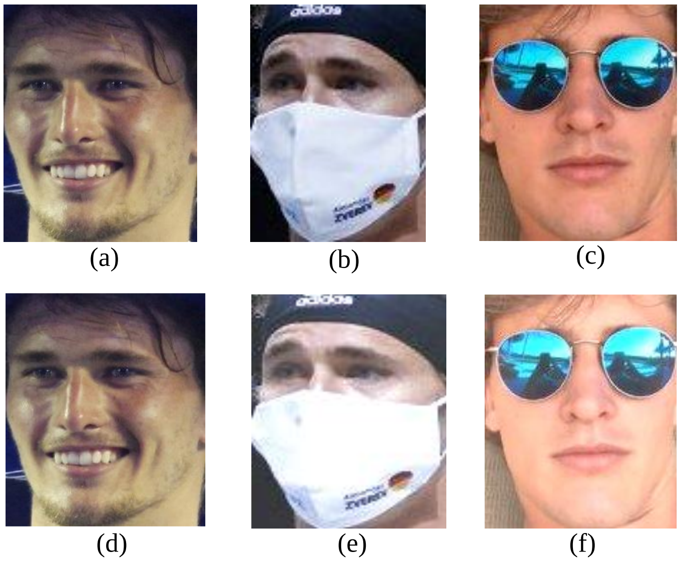

Figure 2 The first row shows the input image (a to c) and the second row shows the pre-processed image (d to f)

B. Texture Pattern Extraction (FSTP)

The normal distribution function based on the probabilistic parameter estimates and the representation of the magnitude difference between the pixels constitute the basis of the FSTP based texture pattern extraction. The overview block design for texture pattern extraction models with a binary matrix format is displayed in figure 3.

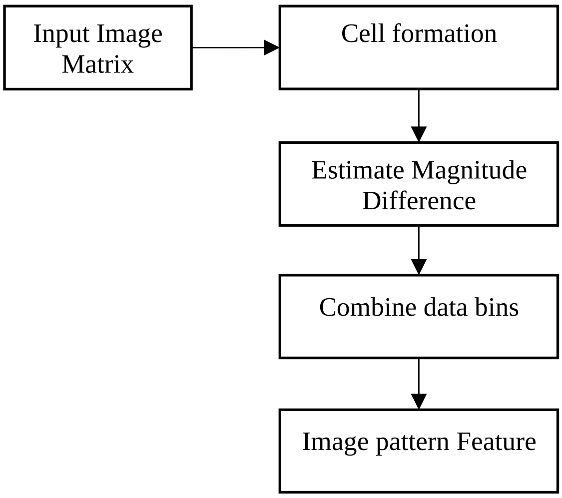

Figure 3 Block diagram of Texture

Algorithm 1: Texture pattern algorithm (FSTP)

Input: Image, I_M
Output: Texture pattern of the image, I_T
Initialize distribution parameter based on the filter coefficient of Gaussian.
Apply equation (1) to convolute the image matrix that is represented as 'G'.
Apply zero padding for the boundaries of image to fill the outer layer of image matrix.
Initialize I_V matrix to represent the mask of the image before projecting to the cell of image.
For i = 3 to p-2 **loop** // The loop 'i' for running mask over row of image from 3 to p-2
  For j = 3 to q-2 **loop** // The loop 'j' for running mask over column of image from 3 to q-2
    Let, $I_V = G(i-2{:}\, i+2, i-2{:}\, i+2)$
    Let, $I_h = G(i,j)$ // Center pixel of cell, 'I_V'.
    Initialize b = 0.
    For k = 1 to length (I_V) **loop**
      Estimate the neighboring combination 'α_k' from (5).
      Calculate the mean difference 'μ_k' for 'k' iteration by (6).
      Calculate the center pixel difference of the cell 'μ_c' from (7).
      Find the sign change with the difference matric and arrange in the vector 'b'.
      Convert the binary stream of data to decimal value and arrange it in the outer matrix as from (9).
    End loop 'k'
    $I_T(i-2, i-2) = b$
  End loop 'y'
End loop 'x'

Algorithm 1 explains the specific steps of the suggested FSTP technique. Let 'I_V' be the 5×5 matrix of the image cell that are to be convolute the image as 'G'. This can be represented as in equation (1).

$$G(i,j) = F(i,j,\sigma) * I_M(i,j) \tag{1}$$

Where, $F(i,j,\sigma)$ – Coefficient Gaussian distribution function.
The Gaussian Coefficient can be estimate by using the equation (2).

$$F(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

Where, 'σ' represent the standard deviation of the distribution function. i and j are the spatial coordinates and indexes of the image matrix.
The gradient of the image matrix can be estimated by the convolution of image with the filter coefficient of

Gaussian distribution function.

Let the magnitude $\left(|H_{ij}|\right)$ and gradient $\left(\alpha(i,j)\right)$ of the convoluted matrix are estimated by the equation (3).

$$|H_{ij}| = \sqrt{H_i^2 + H_j^2},\ \alpha(i,j) = \tan^{-1}\left(\frac{H_i}{H_j}\right) \quad (3)$$

Where, 'i' and 'j' are the cell size

$$H_i = \frac{\partial C_I}{\partial i} \text{ and } H_j = \frac{\partial C_I}{\partial j} \quad (4)$$

The gradients are extracted for the different directions of projections that are referred as $\{+90^0, +45^0, 0^0, -45^0, -90^0\}$.

The neighboring difference, 'α_k' from the image cell was estimated as in equation (5)

$$\alpha_k = \{I_V(k-1{:}k+1, k-1{:}k+1)\} \quad (5)$$

The mean value of the segmented mask can be represented as 'μ_k'. This it identifies the overall boundary pattern of the image. This can be calculated by (6).

$$\mu_k = \frac{1}{8}\sum_{a=1}^{8}\frac{|\alpha_k(a) - I_V(i,j)|}{I_V(i,j)} \quad (6)$$

Similarly, the center of the image cell matrix can be estimated by (7). This can be represented as 'μ_c'.

$$\mu_c = \frac{1}{8}\sum_{a=1}^{8}\frac{|\alpha_k(a) - I_h|}{I_h} \quad (7)$$

Thus, all the combination of boundary and the center of matrix μ_k and μ_c are calculated for the overall image matrix. The difference in image pixel represents the magnitude that are at the edge of the objects. From this, the sign difference is estimated to represent the change in pixels at boundary region. This can be represented as 'S' in (8).

$$S = \begin{cases} 1, & if(\mu_k > \mu_c) \\ 0, & Otherwise \end{cases} \quad (8)$$

From this stream of sign change estimation, the binary identification was represented and arranged it in the array of 'b' in (9).

$$b = b + (2^{k-1} \times S) \quad (9)$$

Thus, binary structure was computed for the entire picture projected by the convoluted image matrix mask. This type of pattern extraction model establishes the picture border that correlates to the depth of cell structure for the occluded face impacted slides. The image's pixel depth was used to generate the histogram, which was then represented as the input image's feature vector. The feature representation of the picture matrix is enhanced by the texture extraction method based on distribution. This applied to the training and testing datasets of obscured face images. Figure 4 and 5 shows the result of texture pattern for the face image. This represents the gradient of image from the pre-processed matrix and the texture pattern at various directions.

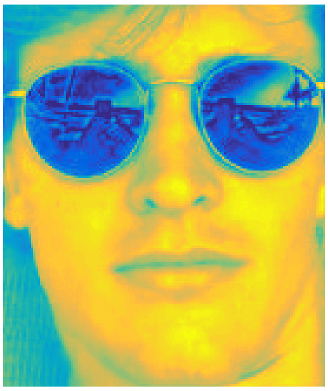

Figure 4 Gradient of image

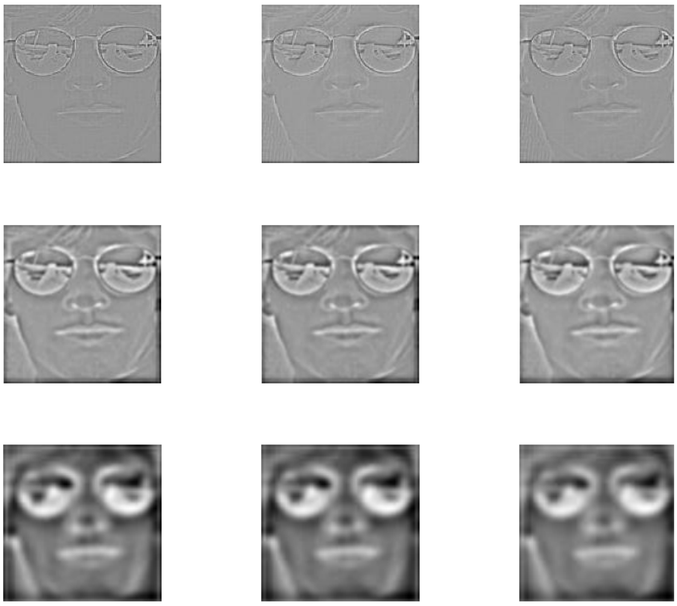

Figure 5 Texture pattern using FSTP

C. *Feature Optimization*

In this, the masking functionality was referred for the feed-back analysis culture and the estimation of error feature attributes. According to the error feature, the decision was framed by updating the weight value of parameters at each iteration of count. The optimization algorithm performs the selection of best feature attributes among the allover feature set. This enhance the prediction accuracy which is by eliminating the non-relevant features in both training and testing features.

Let the general form of switch optimizer can be defined as u(t) which is expressed in equation (10).

$$u(t) = K_p e(t) + K_i \int_0^1 e(\tau)d\tau + K_d \left(\frac{de(t)}{dt}\right) \quad (10)$$

Where, K_p is Particles gain, K_d is the Objective parameter, K_i is the Integral parameter and e(t) represents Error feature from the feedback feature. Also, the parameters of updated feature attribute '*u(t)*'.

The optimizer output m(t) at each iteration instant can be estimate by the equation (11).

$$m(t) = K_p \left(e(t) + \frac{1}{T_i} \int_0^1 e(\tau)d\tau + T_d \left(\frac{de(t)}{dt}\right) \right) + b \quad (11)$$

Where, T_i represents the integral properties, 'b' represents the bias value for the optimizer and T_d represents Derivative pattern feature.

The detailed steps of MMOO parameter identification and tuning is explained in the algorithm 2.

Algorithm 2: *Multi-Model Osprey Optimization (MMOO)*

Input: Input Feature set P_{In}, P_F
Output: Tuning parameters, K_P, K_i and K_d
1. Initialize random particles with reference of $P = [P_{In}, P_F]$,
2. Initialize error pixel from the reference parameter.
3. Calculate weight of particles W = P × R // Where R – Random number.
4. **for** *i = 1 to iter* **do**
5. Calculate the difference in voltage from the current value and with the reference.
6. Update absolute value of the difference.
7. Estimate the feedback error feature at the instant 't' $e(t)$ and update *u(t)* from equation (10).
8. **If** $e(t) \leq e^*(t)$
9. No change in *gain parameters*
10. Else
11. Update K_P, K_i and K_d
12. **End If**
13. **End 'iter' loop**

D. CDNN Classifier

The proposed texture-based image classification model performs the validation process and distribution-type feature representation. The feature vector of the image matrix is supplied so that the prediction model based on the classifier can be trained and tested. Using the Correlative Directional Neural Network classification approach, the proposed occluded face classification method was verified. The classifier estimates the combination weight between the training set and the texting feature vector.

Figure 6 Matching key points

From the training model, this estimates the best connectivity to find the matching key points between the face and the objects that is to occlude the face. From the matching key points, the probability of maximum matching count is recognized, and the related person ID was extracted at the output layer. The classifier is typically applied to a variety of prediction model architectures, such as multi-label and binary classification models. In order to do this, the features must be grouped and arranged in accordance with the combination of relevant feature vectors. In the input layer of classifier, the image feature was segmented into the blocks to evaluate the similarity by batch process. Then based on the ranking of blocks, the hidden layer forms the network by the combination of weight value with respect to the kernel function of classifier. Based on the similarity estimate and the relevant attributes, the features are trained, the range is established, and rules are generated. Based on the matching point, the NN creates a network that reflects the NN training model. Figure 6 shows the representation of matching key points predicted by the classifier to analyse the face feature for person ID.

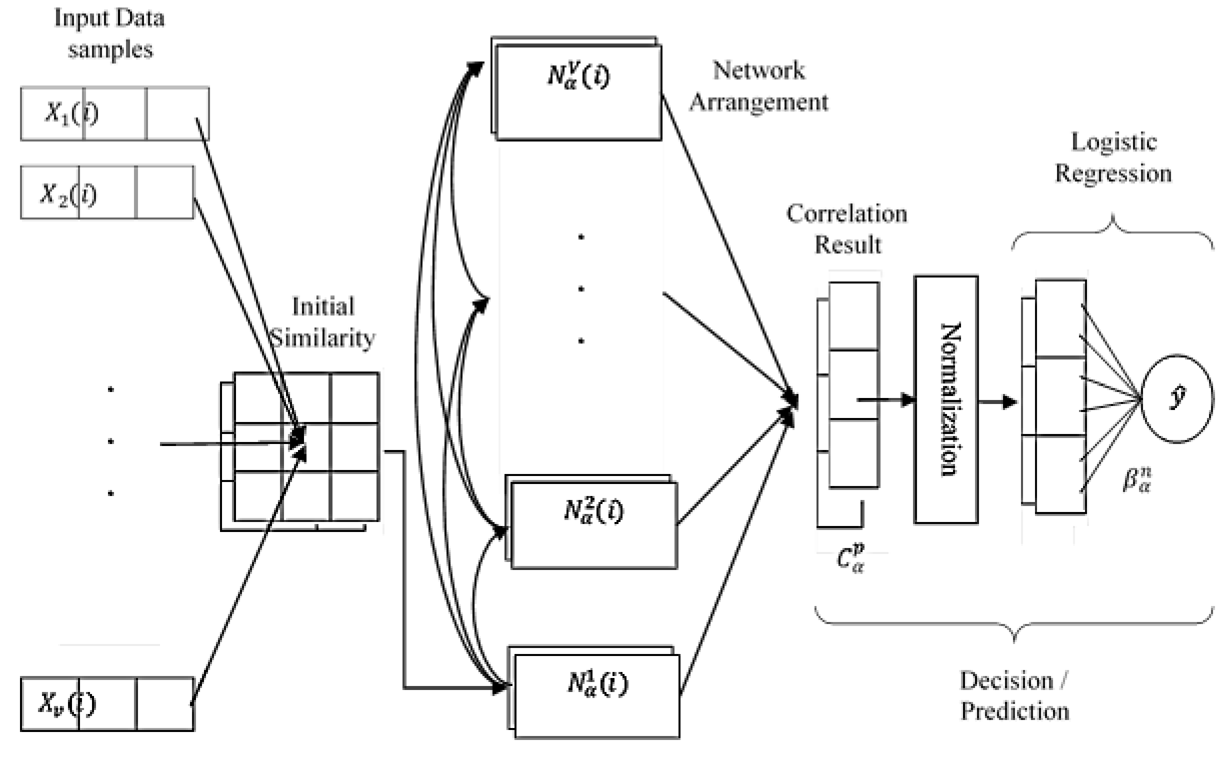

Figure 7 Architecture diagram of Classifier structure

In this study, the NN technique is used to assess the texture feature of the image. The classifier architecture that makes up the NN neuron combination is depicted in figure 6. Here, the '*X*' stands for the feature vector that is fed into the classifier. The similarity prediction was used to originally organize this. From there, the network is constructed based on the feature vector's associated parameters and properties. The class label output is an estimate and prediction of the relevancy between the feature characteristics based on the correlation of the feature matrix. Algorithm 3 describes the algorithm procedure of proposed CDNN classifier.

Algorithm 3: CDNN algorithm

Input: Training set $F_D(s)$
Output: Classified Result $V(k)$
The input series are arranged in the sequential order as,
$F_D(s) = \{T_{D1}(s), T_{D2}(s), \dots, T_{Dm}(s)\}$ // Initialize the feature properties.
In the input layer of classifier, the data sequence can be formed as the matrix as in below equation.
$X_D(s) = \begin{bmatrix} F_{D1}(s) \\ F_{D2}(s) \\ \dots \\ F_{Dm}(s) \end{bmatrix}$ // Matrix arrangement for input layer in the Block separation.
Form the matrix arrangement, the block correlation feature can be estimate by $F\big(X_D(s).X_D^*(s)\big)$. This can be representing as
$F\big(X_D(s).X_D^*(s)\big) = X_D^*.e^{T-T_m}$ // 'T' and 'T_m' represents the attribute values from matrix $X_D(s)$.
Estimate the kernel model of classifier
$K_m = \frac{1}{2^{q-1}}\left(\frac{\sqrt{2q}}{l}\right)^q k_q\left(\frac{\sqrt{2q}}{l}r\right) \quad \forall\, q = 1, 2, \dots, N$ //'r' represents range of feature distance, 'l' represents the length of feature vector.
Estimate the relevancy using kernel function with feature points.
$t_n = F^T\omega_n$ // Texture relevancy. 'ω_n' weight value of attributes.
$u_n = F^T\omega_n$ // Texture relevancy.
Extract the training features and form the network by
$T_r = \{t_1, t_2, \dots, t_n\}$
$X_b = \overline{X_b} + \sum_{i=1}^{N} t_i(d)p^i$
Estimate the matching score for the correlated blocks by
$\widehat{T_s} = \left(\left(X_b^{\bar{d}} - \overline{X_b}\right)^T (P^T)\right)^T$
Where, the relevance factor $X_b^{\bar{d}} \in R^{(T-T_p)M}$ can be written as
$R^{(T-T_p)M} = \widehat{T_s}^{\,T} Q^T + \overline{tt_a}$
Where, 'P' and 'Q^T' – Predicted component.
The predicted label can be representing by
$V(k) = \frac{d_{ij}}{R_j - R_i}$
Where, d_{ij} – Distance matrix for 'i' and 'j' of the relevance matrix 'R'.

IV. Result Analysis

For the testing of Occluded facial images ROF dataset consisting of 3195 neutral images, 1686 sunglass images and 678 masked images of 180 individuals are considered for identifying the person. The data prediction and classification model were implemented in this paper work using MATLAB Script. Sensitivity, specificity, accuracy, recall, accuracy, precision, recall, accuracy, and F1-scores were used to validate the performance of the suggested optimal feature classification model. The current group assignment methods are considered for 70% training and 30% as testing images are contrasted with all of these in [22].

Table 1 Precision and Recall of different classification methods

Methods	Precision (%)	Recall (%)
SVM	71	70
Navie Bayes	89	89
ANN	91	91
PNN	92	92
Densenet	93	93
Proposed	95	94

Table 2 Micro and Macro F1-Score

Methods	Macro F1-Score (%)	Micro F1-Score (%)	Macro Average F1-Score (%)
SVM	70.43	70.67	76
Navie Bayes	89.1	89.3	90
ANN	90.61	90.66	91
PNN	92	92	92
DenseNet	93.35	93.33	94
Proposed	95.72	95.59	95.46

Table 1 shows the comparison result of proposed and other existing methods for the parameters of Precision and Recall in terms of (%). The precision and recall represent the sensitivity of the classification model. In that, the proposed model achieved ~95% compare to others.
Table 2 shows the Macro and Micro averaged as an interpretation for average of Precision and Recall and F1-Score measures to validate the accuracy of image texture analysis.

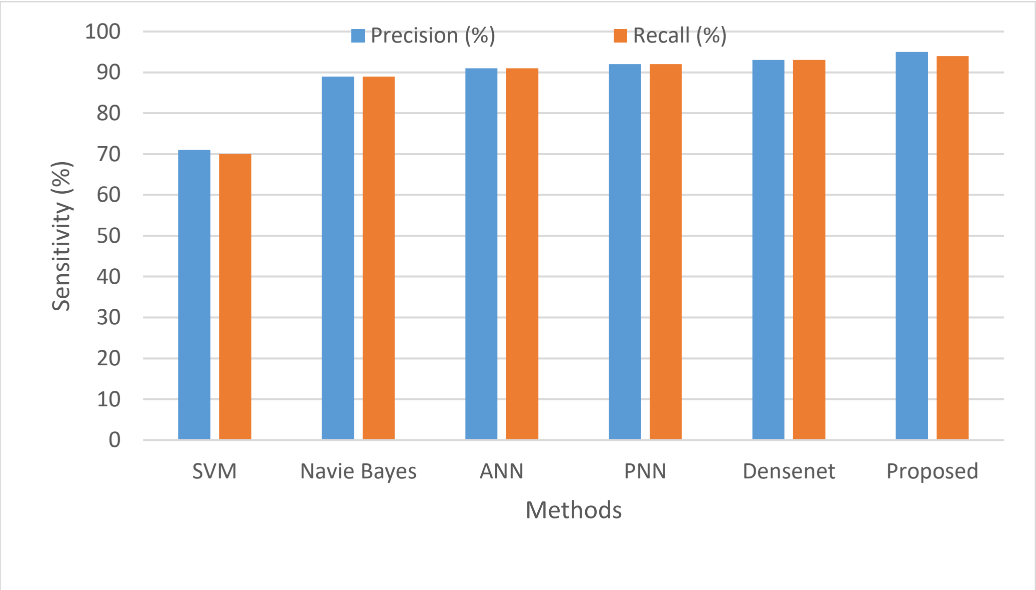

Figure 8 Sensitivity measures

Figure 8 and 9 shows the comparison bar chart of the precision with recall and the F1-Score measures respectively from the existing models referred from [23]. Similarly, the figure 10 shows the comparative chart of Accuracy and Kappa Coefficient. Both parameters are representing the accuracy level in different direction of representation. This is based on observation result and the ground truth of dataset. Figure 11 shows the comparison chart for sensitivity and specificity of occluded face occluded face image classification.

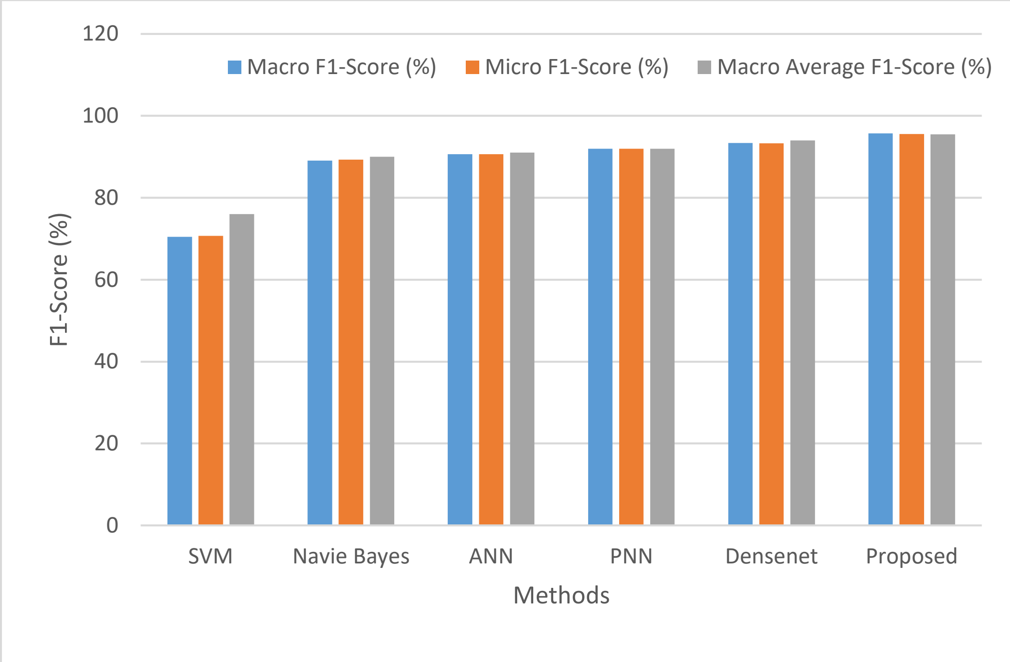

Figure 9 Comparison chart of Micro and Macro F1-Score

Table 3 shows the comparison result of accuracy and kappa-coefficient validation. From this analysis, the Accuracy was noted as ~3% higher than the existing model of image classification from [23].

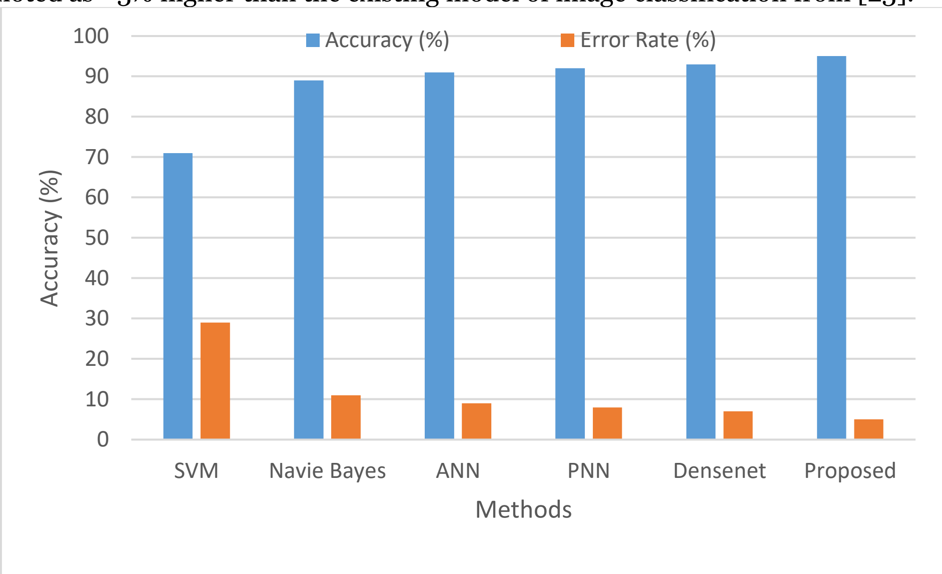

Figure 10 Comparison chart of Accuracy and Error Rate

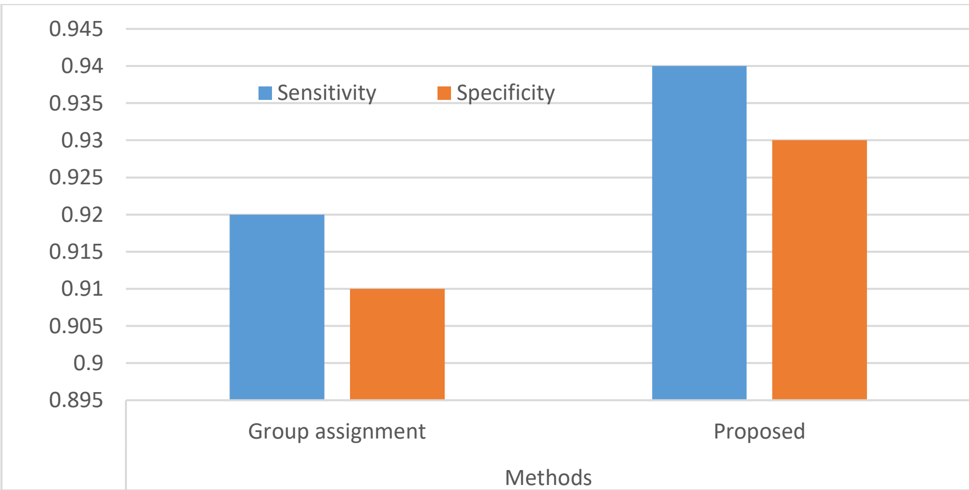

Figure 11 Sensitivity and Specificity comparison chart

Table 4, 5, and 6 shows the performance analysis of proposed work compare to existing model of Group Assignment from [22]. The parameters that are used for the validation are, sensitivity, specificity, precision, F1-Score, Mathews Correlation Coefficient (MCC), Accuracy and Kappa Coefficient. These are all represented as in the graphical chart in figure 12 and 13 for the accuracy validation.

Table 3 Validation of Accuracy and Error Rate

Methods	Accuracy (%)
SVM	71
Navie Bayes	89
ANN	91
PNN	92
Densenet	93
Proposed	95

Table 4 Comparison of Sensitivity and Specificity from [22]

Parameters	Methods	
	Group assignment	Proposed
Sensitivity	0.92	0.94
Specificity	0.91	0.93

Table 5 Comparison of Accuracy and Kappa Coefficient from [22]

Parameters	Methods	
	Group assignment	Proposed
Kappa Coeff	0.91	0.93
Accuracy	0.92	0.94

Table 6 Performance Evaluation from [22]

Parameters	Methods	
	Group assignment	Proposed
Precision	0.92	0.94
F1_Score	0.91	0.928
MCC	0.88	0.91

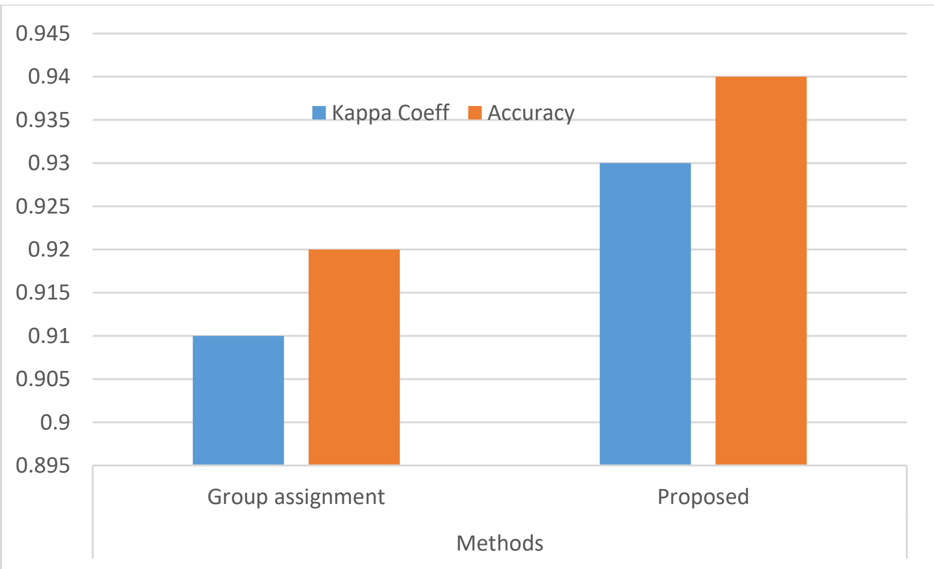

Figure 12 Accuracy comparison chart for proposed and [22]

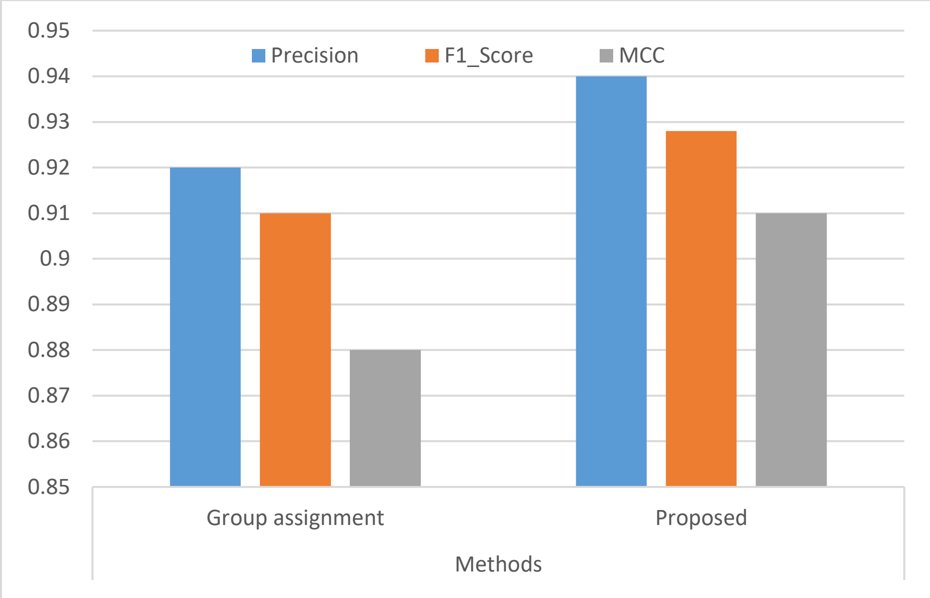

Figure 13 Performance Evaluation of proposed and [22]

The comparison results and the graphs represent the performance of proposed model in data classification and the optimal texture extraction model. From this analysis, the accuracy of proposed model was increased and the sensitivity is ~95% of the overall model compare to other state-of-art methods.

V. Conclusion and Future enhancement

The best texture feature modeling for occluded face recognition was the main emphasis of this paper. By decreasing the ideal size of feature data, this improves classification performance and operational speed. When compared to alternative approaches of texture extraction, the distribution-based image texture analysis yielded a better feature representation of the image overall. Because of this, the Adaptive Gradient has been enhanced in relation to the picture pattern's depth to choose the best feature attributes from the entire image matrix. This was verified by comparing the outcome with other models that were already in use and applying the Correlative Directional Neural Network categorization model. This result from the classification retrieves the person Identification from occluded face. This was justified by the result analysis, which showed that the suggested model increased the performance of occluded face prediction and classification by about 95% of accuracy.

Future work will further improve this by predicting the image's gradients and texture in many directions. By improving the big data processing structure's prediction model, the classification performance was further enhanced.

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