International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Novel Face Tracking and Classification Techniques in Color Images Using Optimized Deep Learning Algorithm

A. Arun Benedict[1*], Ravi Subban[2]

Submitted: 22/01/2023 **Revised:** 12/03/2023 **Accepted:** 07/04/2023

Abstract: To significant applications in robotics, autonomous driving, visual surveillance, object recognition is a crucial study area in pattern recognition. The literature introduces various computer vision methods. There are many difficulties, such as imbalanced dataset & similar shapes of various items. Moreover, they deal with irrelevant feature extraction, which decreases classification performance and enhances calculation. We proposed a totally automatic computer image pipeline in this article. In proposed strategy, original data augmentation is done to balance the categorized objects. A Convolutional Neural Network (CNN) was afterwards taken into consideration and tweaked in accordance with the chosen dataset (Caltech101). The improved model extracts characteristics and was trained via transfer learning. A few unnecessary pieces of information were deleted from the collected characteristics using an Improved Whale Optimization Algorithm (IWOA). The total precision can be enhanced by using auto encoder-based dimensionality reduction, vector-based pixel reconstruction, and loss identification. The categorization procedure for color photos of people is implemented using CNN approach. The accuracy & effectiveness to the proposed method have enhanced according to the performance evaluation results when compared to the existing techniques.

Keywords*: Object Recognition; Feature Extraction; Convolutional Neural Network; Denoising; Image Classification; Optimization Algorithm*

1. Introduction

Biometric systems for person recognition and verification are required as a result of the increasing human elements in next generation technology. There are biometric systems that use fixed physical attributes like the fingerprint, iris, and palm print as well as systems that use behavioral traits like the signature, stride, walking pattern, speech pattern, and face dynamics; the latter are also referred to as soft biometrics [1-2]. Due to differences in head attitude, illumination, age, and facial expression, the issue of face identification in unconstrained situations was difficult [3]. Moreover, accessories, facial hair, and makeup can alter how someone looks. Humans are able to perceive faces with success and almost effortlessly, but computers struggle with the task [4]. To detect faces in connection to contextual knowledge, the human visual system supports sophisticated brain pathways for processing both static and dynamic aspects of the faces [5].

Real applications contain a wider range of face distributions and ambient conditions [6]. Facial recognition algorithms that are tested exclusively within the confines of a single data set will unavoidably develop bias, which skews learning in favor of the data collection's unique traits [7]. Many of the publicly accessible data sets show an under- or overrepresentation of particular types of faces in this restricted setting [8]. There is typically

1Research Scholar, Department of Computer Science, Bharathiar University, Coimbatore, India.
2Associate Professor, Department of Computer Science, School of Engineering and Technology, Pondicherry University, Pondicherry, India.
** Corresponding author's Email: arunbenedict.sjc@gmail.com*

a bias towards younger and older ages. There are some pronounced variances [9]. The necessity to identify faces in forensics and investigations is another application. Several institutions, laboratories, & companies have recently used intruder detection [10]. The basis for face recognition is an understanding of human biology. Face recognition has a considerable advantage over other identifying methods, such as fingerprint, signature, PIN & ID, which all often utilized to self identity & authorization [11]. To be recognized by a fingerprint or a signature, the subject must present the imprint or the signature, correspondingly. However, facial recognition requires no such effort, and the subject may not even be aware that he is being watched [12]. In contrast to ID and PIN, the user also doesn't need to memories anything. It becomes less time-consuming and functions in the same way that people recognize and provide permission to other members of society [13].

Principal component evaluation, Laplacian faces to multi-sub region-based correlation filtered faces, preserve local information, subspace approach, fisher-faces, closest neighbor or and several other techniques should be used for face identification based on eigen faces [14–16]. The use of key feature-based techniques was then widespread among researchers. Originally, SURF-based feature extractors that are scale- and rotation-invariant in planes were proposed [17]. There are normally 64 dimensions in an SURF feature detector. Unsupervised feature learning is an approach for autonomously learning feature demonstrates of raw pixels [18]. Researcher represented features using several feature dictionaries, and value projection matrices were saved for the regions of the face [19].

To attain greater accuracy, feature fusion concatenates various feature spaces into a single feature vector. The retrained deep CNN model AlexNet was used with BoF to solve the FE issue use a bag-of-features, and it achieved competitive accuracy on the difficult database Caltech101 [20].

2. Related Works

The pre-trained deep CNN approach VGG16 was used for learning algorithms. On the difficult classification dataset Caltech101, the pre-trained method, which was trained entirely from scratch, attained an accuracy of 91.66% [21]. To construct the deep CNN method to OR Convolutional architecture, an open-source framework, is combined with the CNN model as a categorization application. To attain competitive accuracy on the Caltech101 database, the categorization programme made use of the GPU facility [22]. Constructed deep learning model Deep feature extraction was accomplished using ResnetNet-50 and VGG16 using associative memory blocks [23]. K-means clustering was used to accomplish unsupervised grouping on associative memory banks.

In image evaluation that employs a multi-temporal images handling method, the narrow bands spectral response reduces performance and decreases classification performance. A most significant challenge in the multi-temporal image is the trade-off between cloud masking & maximum precision [24]. The land state observations provided the enhanced cloud removal performance that allowed the improved method to be used for eliminating the cloud shadow. The use of Land site satellite images has a range of cloud cover with mistakes in the classification and placement of the clouds [25]. The decision tree & random forest algorithm are the greatest tools for removing cloud cover in the NB linked noise tolerant techniques. To improve classification performance, the PC evaluation was performed to specific wavelength bands.

DFF-Net performance was assessed using a dataset of railroad traffic and demonstrated competitive accuracy. The salp swarm algorithm's computational cost was greatly decreased [26] by eliminating pointless characteristics and improving performance. The classification of fused feature vectors with high dimensions was later accomplished using a kernel-based SVM. The VGG16 and VGG19 deep CNN methods were used to extract deep features [27]. The fully linked levels fc6, fc7, and fc8 are used for deep feature extraction. To optimize the features, PCA was used to the retrieved features [28]. The optimized features classified using ensemble classification. Ensemble categorization was used to classify the optimized features. On the benchmark dataset Caltech101, the provided model was assessed and demonstrated competitive accuracy. Inception Recurrent Neural Network is a revolutionary deep learning framework that was released. The proposed method achieved competitive performance on difficult object identification datasets by implanting the RNF & In caption to improve the robustness of a DCC of effective OR.

3. Proposed Methodology

Intelligent deep learning and IWOA are both used for object recognition. Figure 1 presents the overall structure of the proposed framework. The original database was now improved using a data augmentation method, as seen in the following Figure 1. The next phase was choosing a pretrained deep CNN method named DenseNet201 & altering with regard to the categorization stage. Deep FE of the dense level was used this updated model training, which also used transfer learning. The robust features are chosen in the following stage using IWOA. Lastly, machine learning algorithms that are used for final classification are fed the best-selected features.

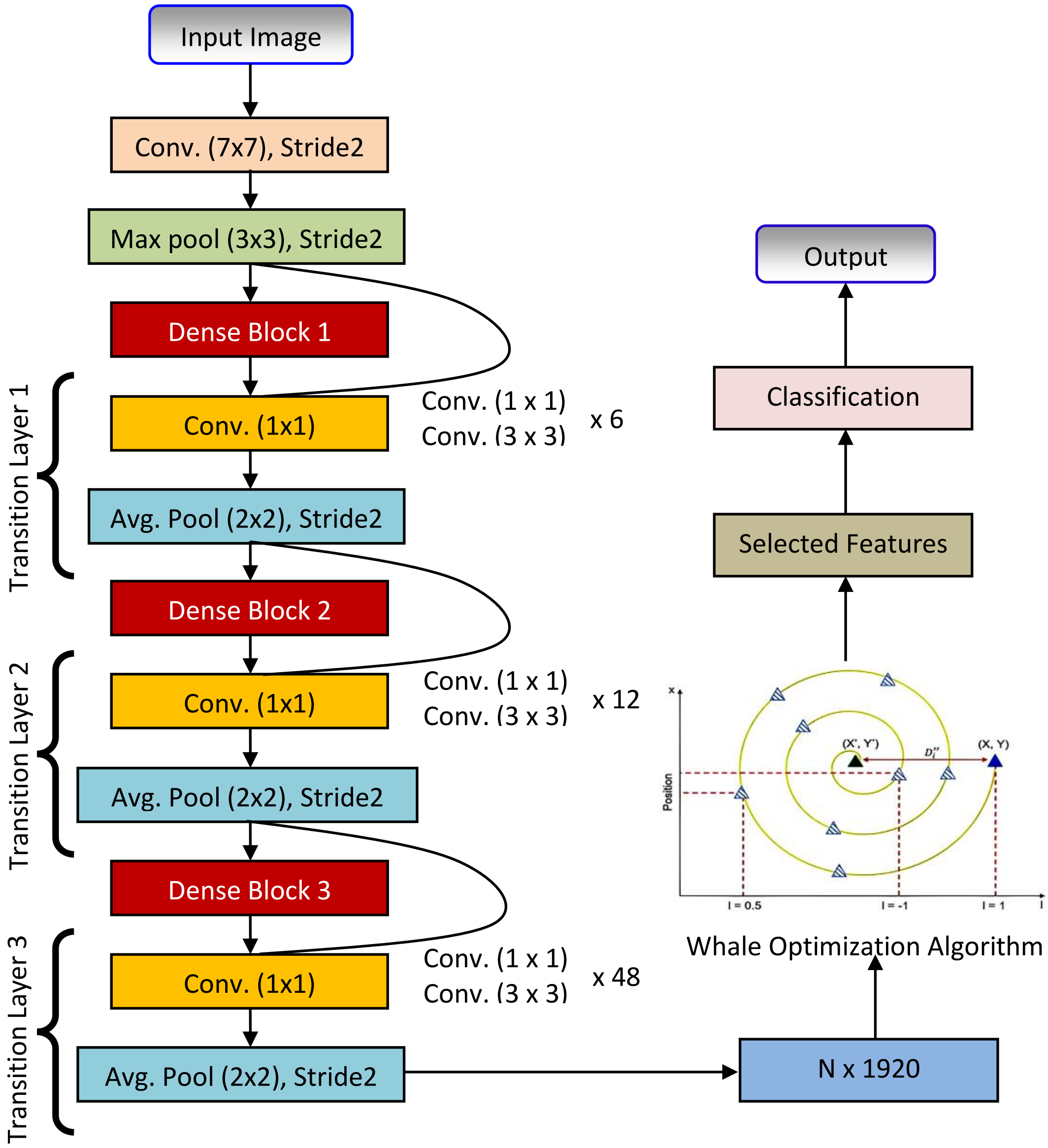

Fig 1: Possible object recognition method

3.1 Edge detection

In reality, the calculation involves three steps. To determine the position of close colour values, the edges are first removed. The next stage is to accurately calculate these places, and the final step involves calculating the colour values. Recognizing edges is the first step in the calculation of a image, and numerous technologies have been developed to do this. The researcher's primary emphasis is on conventional edge identification methods like David Marr's. Mexican Hat Wavelet zero crossings could also be used to represent the margins of a image. The definition of the Mexican Hat Wavelet for multiple channels is x = (x1, . . . , xn), and the equation for the sum of the MHW across various channels was provided in Equation (1). The definition of the MHW for numerous channels is and the equation for their sum across different channels is provided as n.

$$\Delta_x = \sum_{n=0}^{N} \Delta x_n = \Delta(\sum_{n=0}^{N} x_n) \quad (1)$$

The CD algorithm is combined with the David Marr edge identification method to describe the length of edges. A two-dimensional map with a slope at every intersection is used to produce the slope A_{in} in multimedia. This need not be connected to a specific OR method. Nonetheless, correlations with different methods could be made to see how the edge identification method that uses zero crossings performs better on cartoon images. It has been calculated that edges must be recognized to find the pixels for later calculations that fully calculate these coordinates successfully.

3.2 Deep Features Extraction

Convolution, batch normalization, and pooling layers are present in a straightforward deep CNN model. A feature extraction layer like an FC layer and an activation function similar to ReLU are two additional layers. Every CNN model uses its input layer as the first layer, which is then indicates to convolution operations that perform convolution layers to the input image. Dot products of weights and smaller regions are calculated after convolution. ReLU layers carry out the activation process by eliminating the dormant neurons. To prevent data loss, the maintainability to data was essential for the information flow from level. All feature spaces are used to build the classification estimate and the feature spaces at the various layers may be easily distinguished from one another. Given that the layers of the network include gradient loss functions, Dense Net has lower risks of overfiting.

Figure 2 depicts the transfer learning process. The image demonstrates that the source labels are 1000, the source method was DenseNet201 and the source data is ImageNet database. The refined method trained to target data using the source model's expertise. A selection of hyper parameters is made throughout the training phase, such as the number of epochs (200), the learning factor (10), the learning function (stochastic gradient descent), mini-batch size (64), the learning rate (0.001), & the number of iterations (10 per epoch). After this refined model has been trained, activation is utilized to extract features on the global average pooling layer. N 1920 was the measured deep feature vector size after further optimization with IWOA techniques.

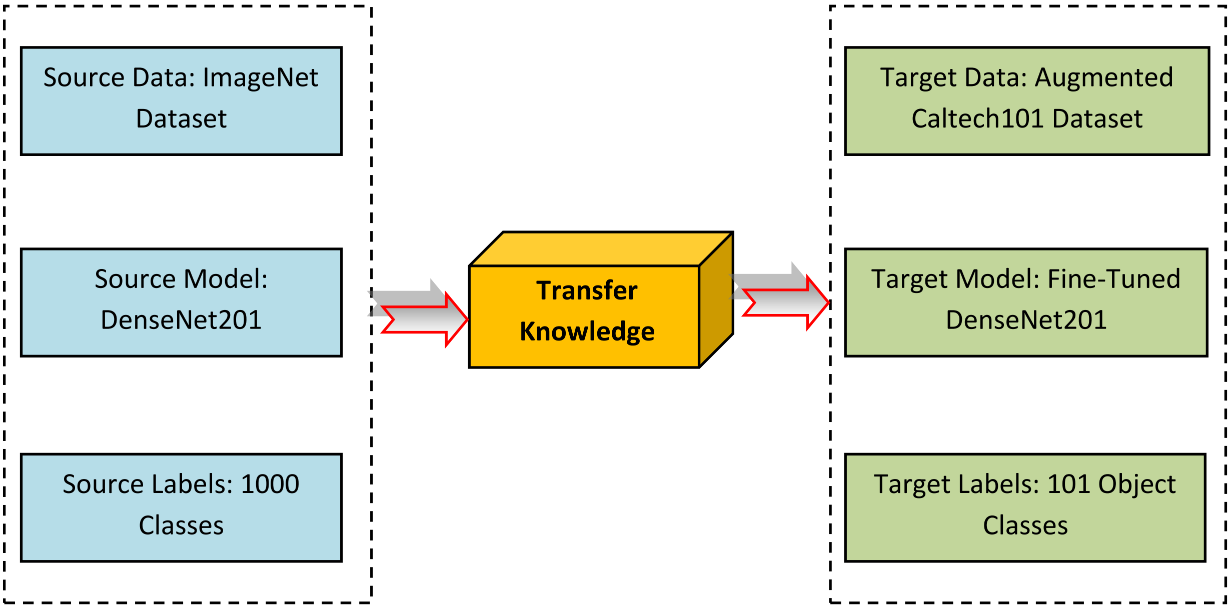

Fig 2: A deep learning model fine-tuned via transfer learning

3.3 Optimization

The convergence value was determined used to proposed methods of determine the criteria value despite the neural network having an optimal function that generates the falling rate. Figure 3 illustrates the optimization method used by the Cauchy mutation operator to develop the detection approach and minimize the natural processing.

IWOA is used to minimize redundant and unnecessary features during feature optimization. There are two steps in the optimization process. The prey was circled in the 1st stage, & the spiral position was maintained. Prey seeking is sometimes referred to the exploration phase, and it depending to the different vector variants. Whale conducts a haphazard attempt to locate the prey based on its location. The search agent flees from the whale because of the whale's location. The vector used by IWOA has random values either higher than & less than 1. The search agent used in the exploration process is chosen at random. Through the reduction of the local optimization problem, random chosen transforms the IWOA into a GSA. A definition of a global search is:

$$\vec{J}(u+1) = \vec{J}_{rand} - \vec{B}.\vec{E} \quad (2)$$

$$\vec{E} = \left|\vec{C}.\vec{J}_{rand} - \vec{J}\right| \quad (3)$$

where $\vec{J}_{rand}$ stands for a randomly chosen whale from the available population.

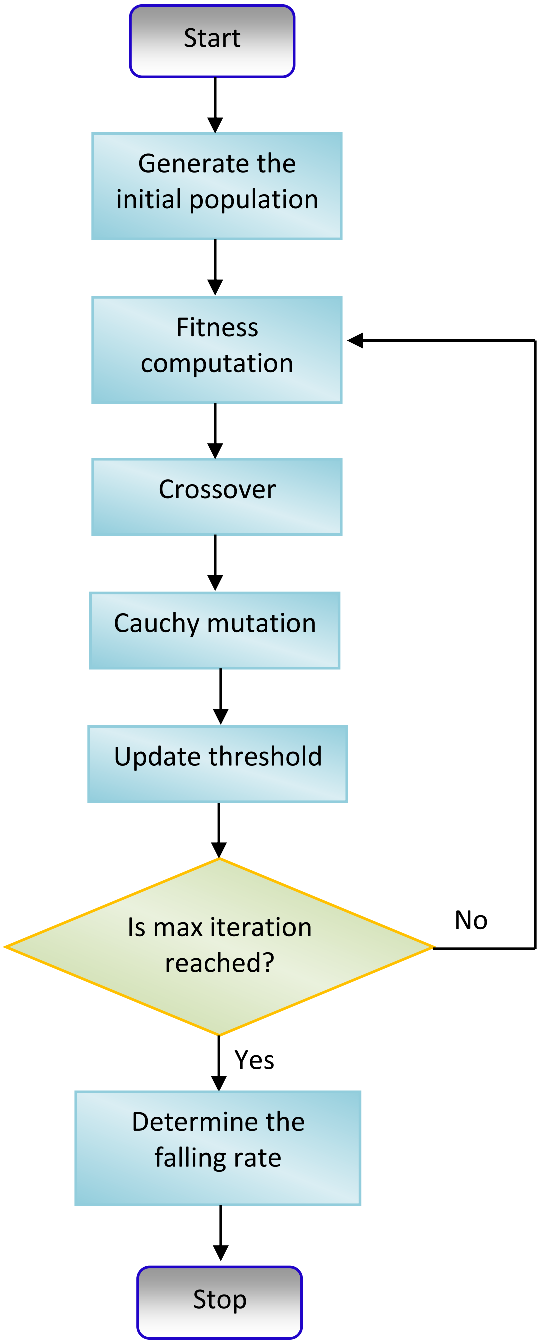

Fig 3: The method of IWOA

To acquire the ideal features, the found optimal falling rate was substituted. The best attributes obtained from the aforementioned procedure are provided to prepare the neural network to identify the character. Figure 4 shows an illustration of a neural network that includes output hidden, and input units and uses the back propagation idea to learning. In Equation (4), the bias function is established

$$i(t) = \beta + \sum_{n=1}^{h}\left(w_{tn} FF_{sc_{tn}}\right) \quad (4)$$

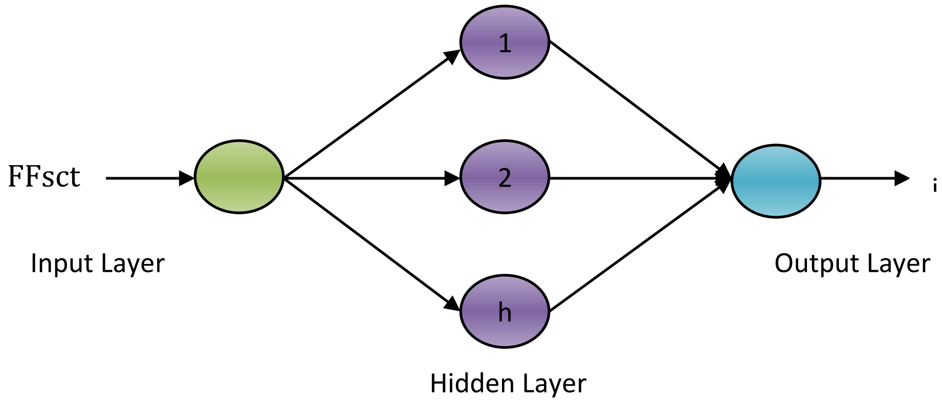

Fig 4: Neural network formation

The proposed approach, which denoised the image using the reduced bands rather than extracting them from the provided latent space, uses the dimensionality reduction methodology. The output layer reconstruction of the image is taken into consideration for the subsequent stage of dimensionality reduction. A statistical approach called the application procedure is used to change a set of previously correlated items into a new set of possibly uncorrelated ones. The original spectral bands could be harder to discern than the image's linear translation utilizing the principle components. Several L spectral bands could be represented by a small number of M components with the greatest degree of variance. Figure 5 illustrates how this capacity is crucial for economic reasons, can save time and space at advanced phases of image processing.

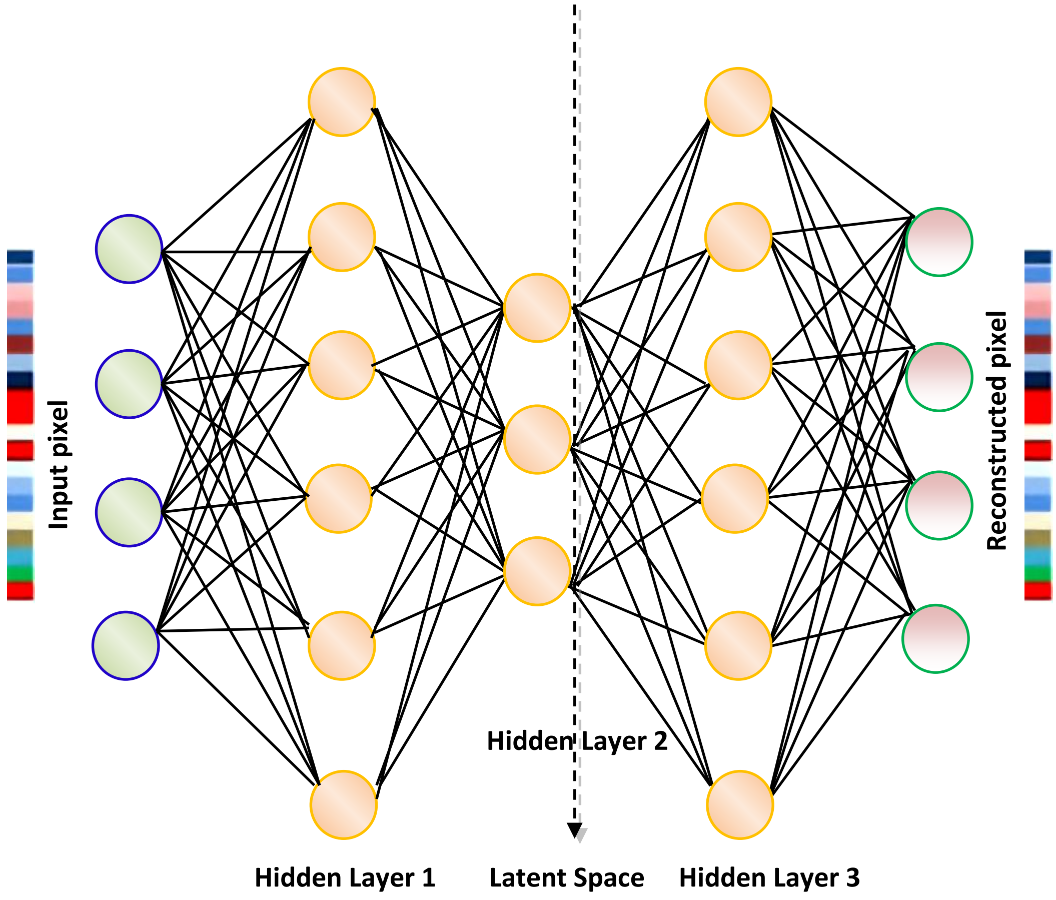

Fig 5: Reconstruction of pixels

The resulting Eigen vectors are arranged such that the first principle element should contain information. The top M elements that can identifying 99% of the input data's are then selected. Figure 6 shows how dimensionality reduction and denoising are used to create the input image & the output image.

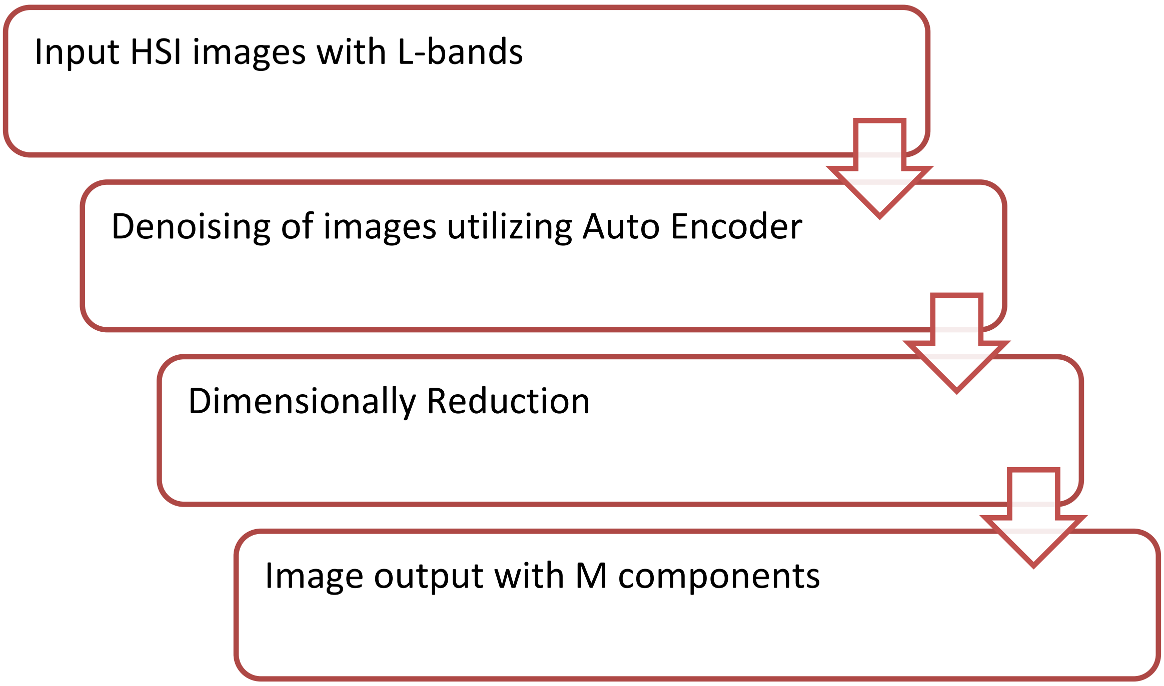

Fig 6: Dimensionality reduction technique

Algorithm – Classification

Step 1: Determine the proper model parameters and construct the classification method using CNN.

Step 2: Differentiate the training samples from the testing samples by setting the database image's pixel values to [0-1].

Step 3: Test method using the learning database until it achieves the required prediction or the allowed criteria mistake.

Step 4: Evaluate the method using test materials. The precision of the evaluation falls short of the desired level, fine-tune the model's hyper parameters and repeat the process.

4. **Results and discussions**

The characteristic of having eyes was thought to be significant for categorization. It was unavoidable to find some human faces where only one eye or even no eye was visible due to the manner our data was collected. According to Figure 7, the left image is the one in which we are interested, whereas the right image was uninteresting for this study. It should be highlighted that compared to the first classification for face defection, the second predictor of eye detection gives more false-positive results. This is primarily due to the target's considerably smaller area, which is easily confused by faces.

Fig 7: Two faces that IWOA extracted

It is proposed to limit the false positive by using geometric restrictions and a shallow CN. The photos are reduced in size for the inference from 500 x 500 pixels to 100 x 100 pixels because the eyes are smaller. Eye areas are identified by the 2nd HC classification. Many black dots on the faces of people to the backdrop grid are classified by the detector as eyeballs, whereas the red areas are false positives. The output is then rescaled to suit the original image after the face has been found on the shrunk image. The inference process is depicted in Figure 8.

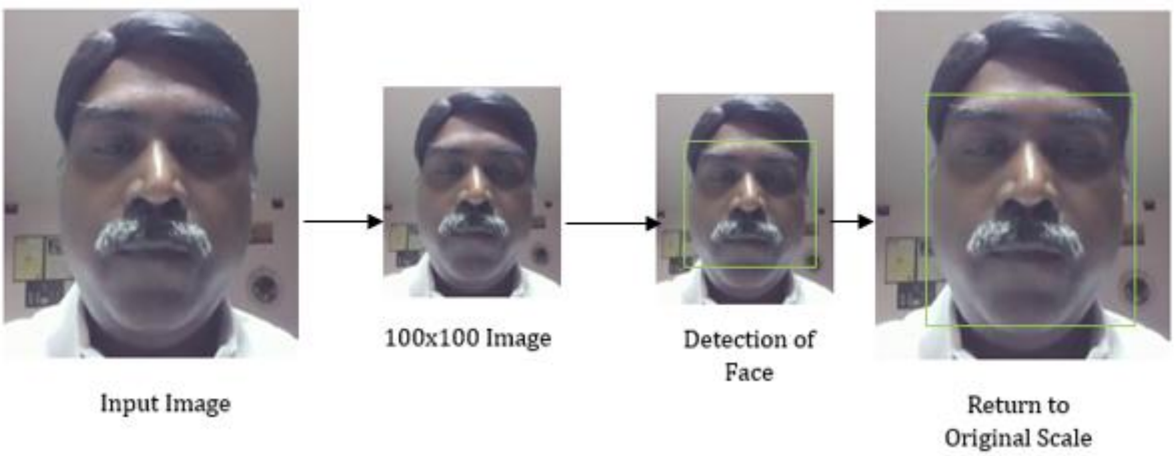

Fig 8: Face Detection with IWOA extracted

The resolution was set to 10 x 10 due to the fact that the eyes are smaller than the faces. The photos are reduced in size for the inference from 500 x 500 pixels to 100 x 100 pixels because the eyes are smaller. Eye areas are listed by the second Haar Cascade classification. The eye detector produces more false positives than the face sensor shown in Figure 9.

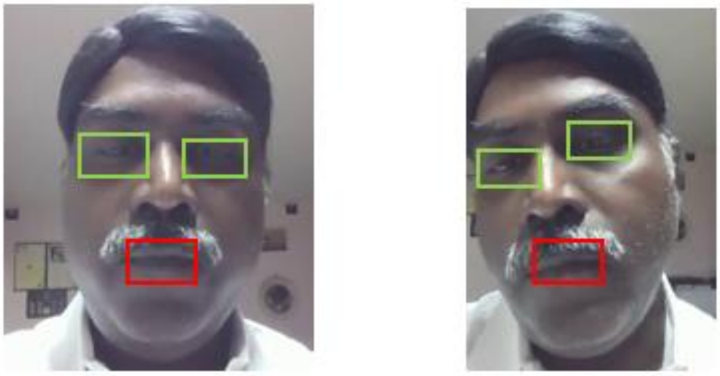

Fig 9: Illustrations of false positive eye detection results.

The third row of Figure 10 demonstrates that the eyes appear to be the most crucial feature for categorization. It is understandable to the information extraction method makes sure that both eyes were always open, providing the network with accurate data from which train. To the eyes, other features, such as the black dots on the face, also seem to be significant in the choice. There is no proof that the network picks up information from its surroundings.

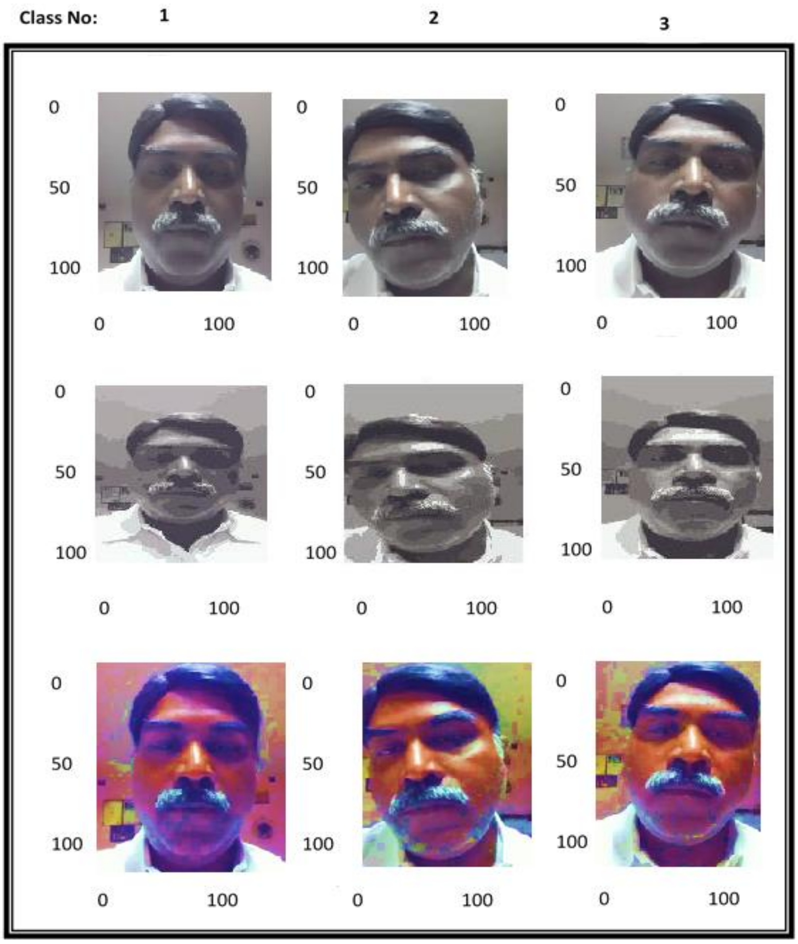

Fig 10: A visualization of the network's learning locations

The majority of the footage does not need to be stored unless anomalous events are noticed and tracking the raw data is necessary. Moreover, they believe that a single camera is capable of performing several tasks. For instance, in addition to the footage, face recognition, may be understand human behavior, which could be used to spot sick people and unusual occurrences such sow squash human lets. Edge computing allows for the addition of ever-growing features with essentially no additional hardware expenditure. As a result of their benefits in terms of accessibility, configuration, and extensibility, digital cameras are appealing to include in future swine farms.

4.1 Evaluation

In the experiments, various cross-validation ratios for training and testing are taken into account. Examining the differences in accuracy and rendering performance of the proposed frame work is the primary goal of various tests. The proposed approach used a 10-fold cross-validation and a 70:30 method in this experiment. Table 1 lists the classification outcomes for various classifiers. To execute the recognition task, various classifiers are used, & a robust was chosen based on precision. The proposed framework is validated using different efficiency evaluation metrics like FNR, computing time & precision. The best classification accuracy is attained with an ESD classifier of 92.9% (7.3%). In Figure 11, the confusion matrix for our strategy to classifying ESDs using 10-fold cross-validation and 70:30 approaches is displayed.

Table 1: Classification using 70:30 techniques at 10-fold cross-validation

Model	Metrics		
	Accuracy (%)	FNR (%)	Time (sec)
IWOA-CNN	93.1	7.3	663
LDA	88.5	11.9	105
L-SVM	85.2	15.3	2476
Q-SVM	86.5	14.3	3385

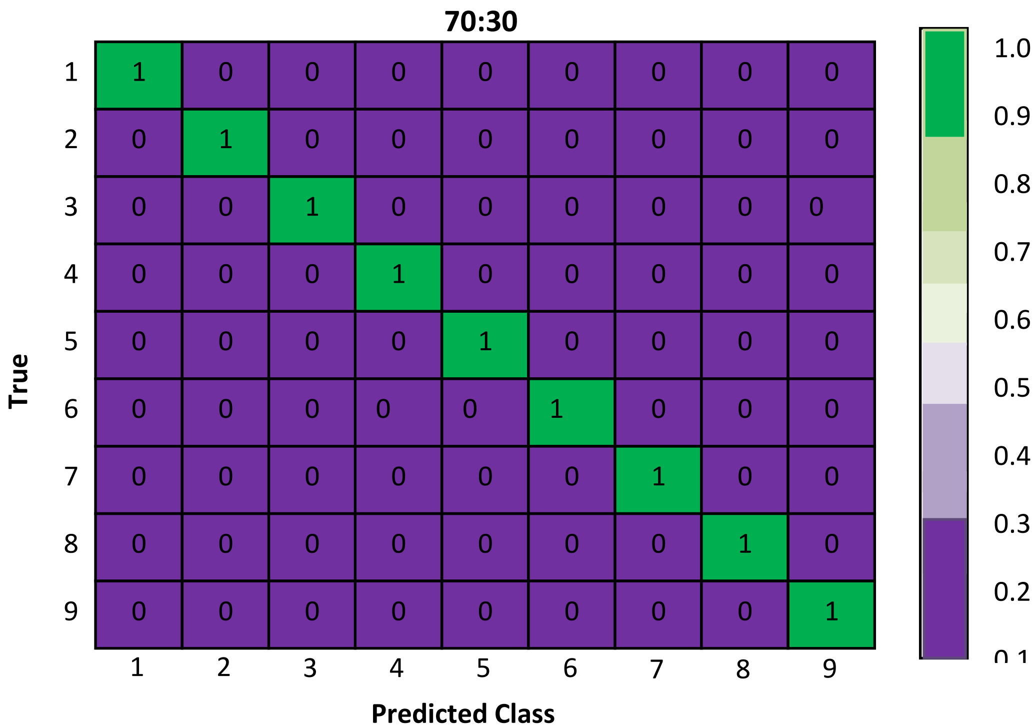

Fig 11: 10-fold and 70:30 approach confusion matrix

The proposed framework is used in this experiment with an 80:20 testing to 10-fold cross-verification ratio. Table 2 displays the classification results obtained using this method. Several classifiers are run to evaluate the classification accuracy. The outcomes indicate that IWOA-CNN was the most accurate classification, of 93.1% accuracy rate, while L-SVM is the least accurate, with an 84.2% accuracy rate. Figure 12 displays the robust classifier's confusion matrix in terms of accuracy. Although the accuracy is higher in this experiment than in Experiment 1, the computing time is higher.

Table 2: Classification using the 80:20 method at 10-fold cross validation

Model	Metrics		
	Accuracy (%)	FNR (%)	Time (sec)
IWOA-CNN	93.9	6.5	857
LDA	91.2	9.1	97.547
L-SVM	86.5	13.9	2658
Q-SVM	86.7	13.5	3442

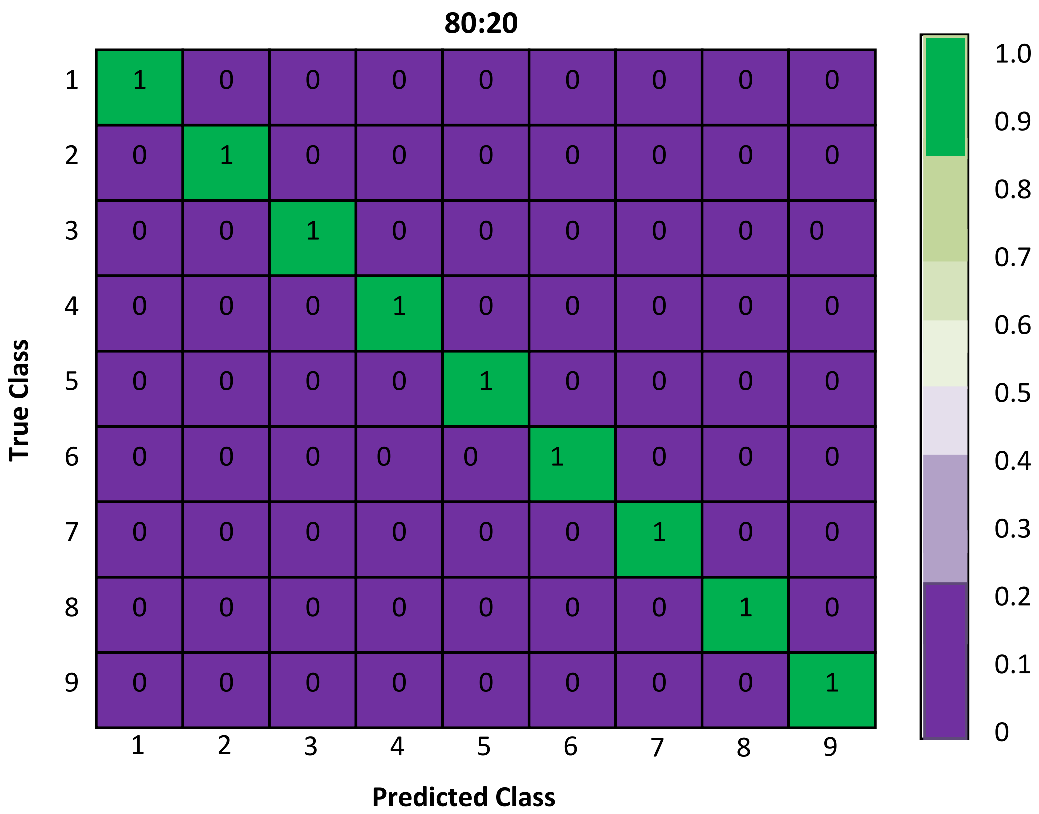

Fig 12: Confusion matrix employing an 80:20 method at 10-fold cross-validation

The extensive trials showed how our proposed classification framework performed while employing various evaluating to learning ratios at various cross-validation method. This section elaborates on the classification performance of the proposed methodology and its comparison to cutting-edge techniques. They used different testing & training techniques, such as 70:30 and 80:20, as well as cross-validation levels like 10-fold. The 80:20 technique was used to attain the best prediction, which was 93.7% to 10-fold cross validation. For each experiment, the IWOA-CNN classifier produced superior results.

Furthermore, the performance IWOA-CNN classification was evaluated against a number of pertinent methods.

For each experiment, the IWOA-CNN classifier produced superior results. Furthermore, the performance IWOA-CNN classification was evaluated against a number of pertinent methods. Furthermore, Figure 13's overall representation demonstrates how much better the proposed technique works with the ESD classifier. Figure 14 illustrates the effects of the characteristic optimization process final. According to this graph, the proposed optimization step improves each classifier's performance by an average of 3%.

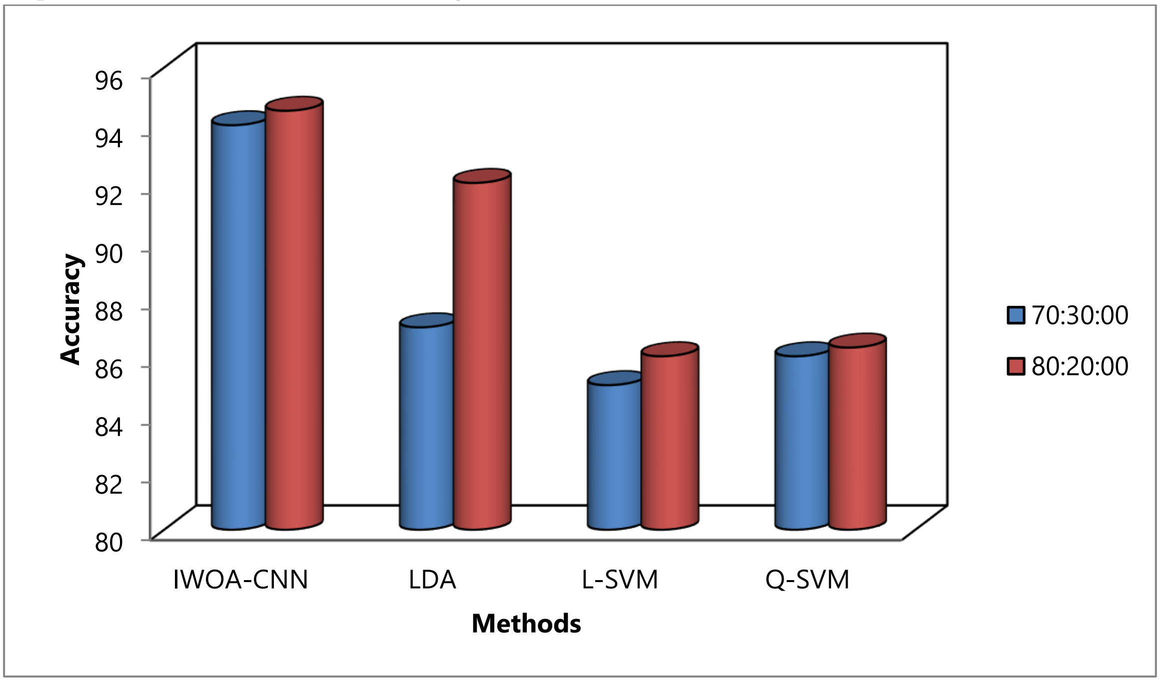

Fig 13: Results of 10-fold cross-verification at various evaluations and testing ratios classification

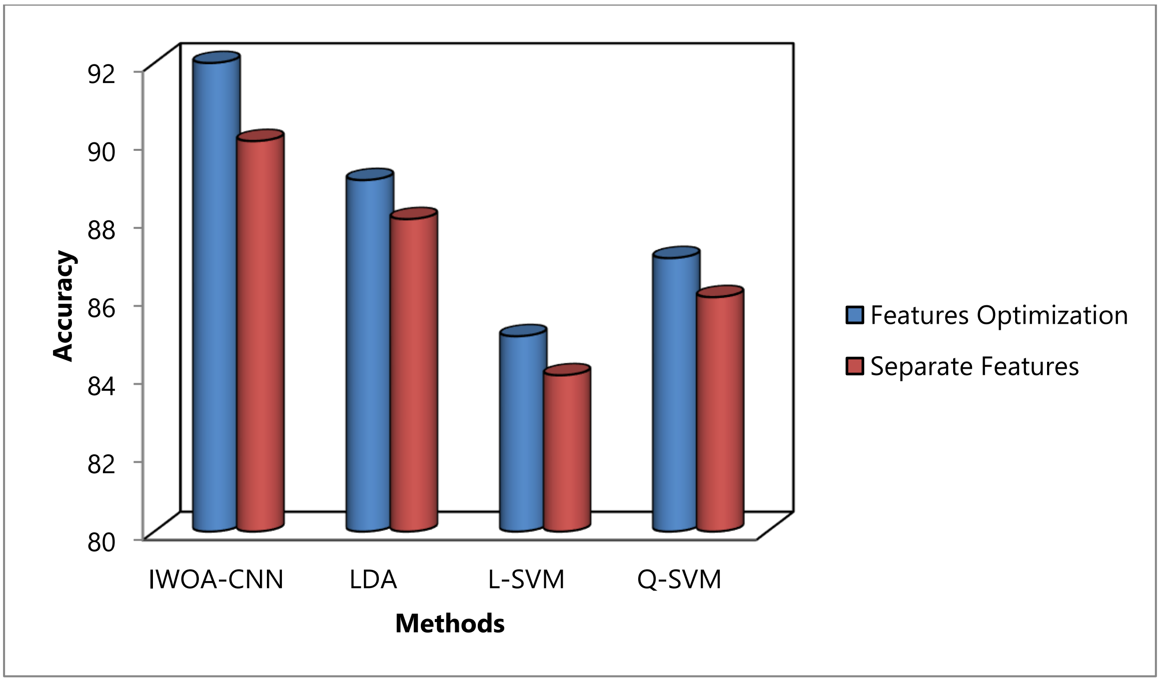

Fig 14: Accuracy of IWQA-CNN

5. Conclusion

Researchers used the pretrained Densenet201 CNN model for our deep learning algorithm based on less parameter. Researchers suggest an IWOA-CNN to choose the best features because the characteristics extracted to this method were in the highest dimension. In particular, Haar feature-based cascade classifiers are used to extract human faces and eyes, and a method evaluating using classifier cross-entropy loss function & directed by AO is used to recognize faces. It has shown 380 that the NN benefits of fascinating characteristics like eyes and particular markers on the human face to the research of activation maps & saliency. The 80:20 approach's accuracy is improved by the features taken from the modified IWOA-CNN. Also, the outcomes of the 70:30 technique & 10-fold cross-validation are improved by proposed framework. The data augmentation stage is the main weakness of this approach. By using this phase, it is possible to identify features that are redundant despite efforts to delete them in the feature selection process. The proposed framework will be taken into consideration for real-time object recognition in next investigations. Additionally, because of its lightweight construction, Efficient Net will be taken into consideration for feature extraction.

References

[1] Khan, A. A., Shaikh, A. A., Shaikh, Z. A., Laghari, A. A., & Karim, S. (2022). IPM-Model: AI and metaheuristic-enabled face recognition using image partial matching for multimedia forensics investigation with genetic algorithm. *Multimedia Tools and Applications*, *81*(17), 23533-23549.

[2] Bhushan, S., Alshehri, M., Agarwal, N., Keshta, I., Rajpurohit, J., & Abugabah, A. (2022). A novel approach to face pattern analysis. *Electronics*, *11*(3), 444.

[3] Patil, N. (2022). Improved face recognition method using SVM-MRF with KTBD based KCM segmentation approach. *International Journal of System Assurance Engineering and Management*, 1-12.

[4] Ullah, R., Hayat, H., Siddiqui, A. A., Siddiqui, U. A., Khan, J., Ullah, F., ... & Karami, G. M. (2022). A real-time framework for human face detection and recognition in cctv images. *Mathematical Problems in Engineering*, *2022*.

[5] Gupta, S., Thakur, K., & Kumar, M. (2021). 2D-human face recognition using SIFT and SURF descriptors of face's feature regions. *The Visual Computer*, *37*, 447-456.

[6] Cook, C. M., Howard, J. J., Sirotin, Y. B., Tipton, J. L., & Vemury, A. R. (2019). Demographic effects in facial recognition and their dependence on image acquisition: An evaluation of eleven commercial systems. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, *1*(1), 32-41.

[7] Merler, M., Ratha, N., Feris, R. S., & Smith, J. R. (2019). Diversity in faces. *arXiv preprint arXiv:1901.10436*.

[8] Sun, Y., Ren, Z., & Zheng, W. (2022). Research on face recognition algorithm based on image processing. *Computational Intelligence and Neuroscience*, *2022*.

[9] El-Melegy, M. T., & Kamal, A. T. (2022). Linear Regression Classification in the Quaternion and Reduced Biquaternion Domains. *IEEE Signal Processing Letters*, *29*, 469-473.

[10] Raju, K., Chinna Rao, B., Saikumar, K., & Lakshman Pratap, N. (2022). An Optimal Hybrid Solution to Local and Global Facial Recognition Through Machine Learning. *A Fusion of Artificial Intelligence and Internet of Things for Emerging Cyber Systems*, 203-226.

[11] Sunitha, G., Geetha, K., Neelakandan, S., Pundir, A. K. S., Hemalatha, S., & Kumar, V. (2022). Intelligent deep learning based ethnicity recognition and classification using facial images. *Image and Vision Computing*, *121*, 104404.

[12] Singhal, P., Srivastava, P. K., Tiwari, A. K., & Shukla, R. K. (2022). A Survey: Approaches to facial detection and recognition with machine learning techniques. In *Proceedings of Second Doctoral Symposium on Computational Intelligence:*

DoSCI 2021 (pp. 103-125). Springer Singapore.
[13] Song, Z., Nguyen, K., Nguyen, T., Cho, C., & Gao, J. (2022, January). Spartan face mask detection and facial recognition system. In *Healthcare* (Vol. 10, No. 1, p. 87). MDPI.
[14] Prasanna, G. S., Pavani, K., & Singh, M. K. (2022). Spliced images detection by using Viola-Jones algorithms method. *Materials Today: Proceedings*, *51*, 924-927.
[15] Wang, Y., & Wu, Q. (2022, March). Research on face recognition technology based on PCA and SVM. In *2022 7th International Conference on Big Data Analytics (ICBDA)* (pp. 248-252). IEEE.
[16] Khaki, S., Safaei, N., Pham, H., & Wang, L. (2022). Wheatnet: A lightweight convolutional neural network for high-throughput image-based wheat head detection and counting. *Neurocomputing*, *489*, 78-89.
[17] Li, M., Huang, B., & Tian, G. (2022). A comprehensive survey on 3D face recognition methods. *Engineering Applications of Artificial Intelligence*, *110*, 104669.
[18] Canal, F. Z., Müller, T. R., Matias, J. C., Scotton, G. G., de Sa Junior, A. R., Pozzebon, E., & Sobieranski, A. C. (2022). A survey on facial emotion recognition techniques: A state-of-the-art literature review. *Information Sciences*, *582*, 593-617.
[19] Raharja, N. M., Fathansyah, M. A., & Chamim, A. N. N. (2022). Vehicle parking security system with face recognition detection based on eigenface algorithm. *Journal of Robotics and Control (JRC)*, *3*(1), 78-85.
[20] Rusia, M. K., & Singh, D. K. (2023). A comprehensive survey on techniques to handle face identity threats: challenges and opportunities. *Multimedia Tools and Applications*, *82*(2), 1669-1748.
[21] Keshri, A., Singh, A., Kumar, B., Pratap, D., & Chauhan, A. (2022). Automatic detection and classification of human emotion in real-time scenario. *Journal of IoT in Social, Mobile, Analytics, and Cloud*, *4*(1), 41-53.
[22] Kim, M., Jain, A. K., & Liu, X. (2022). Adaface: Quality adaptive margin for face recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 18750-18759).
[23] Osipov, A., Pleshakova, E., Gataullin, S., Korchagin, S., Ivanov, M., Finogeev, A., & Yadav, V. (2022). Deep learning method for recognition and classification of images from video recorders in difficult weather conditions. *Sustainability*, *14*(4), 2420.
[24] Ismael, Y. S., Shakor, M. Y., & Abdalla, P. A. (2022). Deep Learning Based Real-Time Face Recognition System. *NeuroQuantology*, *20*(6), 7355-7366.
[25] Yadav, N., Alfayeed, S. M., Khamparia, A., Pandey, B., Thanh, D. N., & Pande, S. (2022). HSV model-based segmentation driven facial acne detection using deep learning. *Expert Systems*, *39*(3), e12760.
[26] Chaabane, S. B., Hijji, M., Harrabi, R., & Seddik, H. (2022). Face recognition based on statistical features and SVM classifier. *Multimedia Tools and Applications*, *81*(6), 8767-8784.
[27] Malik, A., Kuribayashi, M., Abdullahi, S. M., & Khan, A. N. (2022). DeepFake detection for human face images and videos: A survey. *IEEE Access*, *10*, 18757-18775.
[28] Roa'a, M., Aljazaery, I. A., ALRikabi, H. T. S., & Alaidi, A. H. M. (2022). Automated Cheating Detection based on Video Surveillance in the Examination Classes. *iJIM*, *16*(08), 125.