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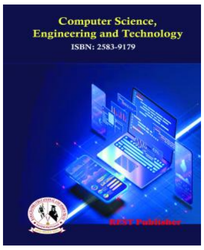

Face Recognition Using IOT Devices in Smart Cities Using Lamstar Network

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Abstract. This study proposes a face recognition system using IoT devices in smart cities, leveraging the Large Memory Storage and Retrieval (LAMSTAR) Neural Network (NN). Traditional face recognition methods struggle with accuracy due to poor feature extraction and high computational complexity. To address this, facial images are captured using IoT sensors and pre-processed using advanced filtering techniques. Key facial features are extracted and classified using the LAMSTAR network, which enhances recognition accuracy by efficiently storing and retrieving facial patterns. This system improves security, real-time monitoring, and access control in smart cities, ensuring efficient and adaptive face recognition.
Keywords: Face recognition, IoT devices, smart cities, LAMSTAR network, Pixel, Image

1. INTRODUCTION

The rapid development of smart cities has introduced advanced technologies to improve urban living, enhance security, and ensure efficient resource management. One of the key components of a smart city is its ability to provide real-time surveillance and secure identity verification through automated facial recognition systems [1]. Traditional security methods, such as ID cards, passwords, and fingerprint recognition, often prove inadequate due to security breaches, human errors, and inefficiencies in large-scale implementations. In contrast, AI and IoT-based facial recognition systems offer a more efficient, scalable, and contactless solution for identity verification and security monitoring in smart cities [2].

Facial recognition technology has gained significant traction in various applications, including public security, law enforcement, banking, and healthcare. However, despite its widespread adoption, existing face recognition systems face challenges in accuracy, computational efficiency, and adaptability under diverse environmental conditions. These challenges stem from poor feature extraction, high computational complexity, and difficulty in recognizing faces under varying lighting conditions, occlusions, and pose variations [4]. Addressing these limitations is crucial for deploying an operative and reliable facial recognition system in a smart city environment [3].

The combination of Artificial Intelligence (AI) and the Internet of Things (IoT) has transformed the capabilities of facial recognition. IoT-based devices, such as smart surveillance cameras and biometric sensors, enable real-time data collection [5], while AI-driven algorithms process and analyse facial features with greater precision. By leveraging these technologies, an intelligent facial recognition system can enhance security, optimize urban mobility, and improve the overall connectivity within smart cities.

2. LITERATURE REVIEW

Facial recognition technology has become an essential tool in various fields, particularly in security, surveillance, access control, and smart city infrastructure. As urban environments continue to grow, the demand for real-time, accurate, and scalable face recognition systems has increased significantly [6]. However, traditional and even some modern facial recognition methods face limitations in terms of accuracy, computational efficiency, and adaptability to diverse environmental conditions. This literature survey explores the existing research and methodologies in facial recognition, their limitations [7], and how IoT and advanced neural networks, such as LAMSTAR, offer a more effective solution.

Traditional Machine Learning (ML) Approaches in Face Recognition: Early facial gratitude schemes trusted deeply on traditional machine learning techniques such as Support Vector Machines (SVMs), Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA)[1][7]. PCA is one of the initial approaches in face recognition, PCA reduces dimensionality by extracting the most significant features from facial images. However, PCA struggles with illumination variations, facial occlusions, and pose changes, which significantly impact recognition accuracy. LDA improves upon PCA by maximizing class separability, but it still suffers from computational inefficiency when dealing with large-scale facial databases. SVMs have been used for classification tasks in facial recognition, but their effectiveness is limited in complex environments with large datasets due to their high computational cost. While these methods were useful in early face recognition applications, their inability to handle real-time recognition tasks in dynamic environments, such as smart cities, made them less practical.

Deep Learning (DL) based Face Recognition: The introduction of DL revolutionized facial recognition by enabling more robust feature extraction and classification. Two of the most commonly used DL models for facial recognition are Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) [1][8]. CNNs have demonstrated outstanding presentation in image recognition and feature extraction. Models such as FaceNet, DeepFace, and VGGFace have significantly improved face recognition accuracy. However, CNNs require high computational properties and extensive training datasets, manufacture them less efficient for real-time applications in IoT-enabled smart city environments. Recurrent Neural Networks (RNNs): While RNNs have been explored for facial recognition in video-based surveillance, their sequential nature makes them computationally expensive, limiting their application in large-scale smart city infrastructures. Despite their high accuracy and feature-learning capabilities, deep learning models often demand powerful GPUs, high memory storage, and large-scale labeled datasets, which pose challenges in real-time, distributed IoT environments.

IoT-Integrated Facial Recognition: To enhance real-time processing and scalability, researchers have explored integrating IoT with facial recognition systems. IoT-based facial recognition leverages edge computing, cloud-based architectures, and distributed sensor networks to capture and process facial data efficiently. Edge Computing: By processing data locally on IoT devices (e.g., smart cameras, biometric sensors) before sending it to central servers, edge computing reduces latency and network congestion. However, computational limitations at the edge remain a challenge.Cloud-Based Architectures: Cloud computing allows for centralized storage and processing of facial recognition data, enabling large-scale analysis. However, cloud-based systems suffer from privacy concerns, latency issues, and dependence on a stable network.While IoT integration has improved real-time facial recognition and large-scale data collection, existing deep learning models still struggle with computational efficiency, requiring a more adaptive and memory-efficient approach.

The LAMSTAR - NN for Face Recognition: The LAMSTAR - NN has appeared as a promising alternative for attractive facial recognition accuracy and efficiency in IoT-enabled smart cities. LAMSTAR is a self-organizing, modular, and memory-efficient neural network that provides several advantages[3][9]:Self-Learning Capability: LAMSTAR continuously adapts to new data, improving its recognition accuracy over time without requiring frequent retraining.Fast Decision-Making: Unlike deep learning models that require extensive training and computational power, LAMSTAR efficiently processes facial patterns in real time.Efficient Memory Storage: Its hierarchical structure allows for the efficient retrieval of facial data, reducing the need for high computational resources.Studies have shown that LAMSTAR-based facial recognition systems outperform traditional ML models and DL networks in terms of speed, accuracy, and flexibility to varying conditions (e.g., poor lighting, occlusions, and different facial expressions).

From the literature review, it is evident that traditional ML models fail to meet the real-time accuracy and computational efficiency required for large-scale smart city applications [1]. While deep learning models offer higher accuracy, their computational complexity makes them unsuitable for IoT-enabled, real-time facial recognition. IoT-integrated facial recognition has improved real-time monitoring and security, but existing models still struggle with handling large-scale data efficiently[7]. The LAMSTAR neural network emerges as a strong alternative, providing a self-learning, memory-efficient, and fast-processing solution. By leveraging the strengths of IoT and LAMSTAR[8], this research contributes to the growth of a more robust, scalable, and adaptive facial recognition system, ensuring enhanced security and efficiency in next-generation smart cities.

3. RESEARCH METHODOLOGIES

The initial step in the task is noise elimination [10], and this is carried out using the Perona-Malik dispersion method. Before reducing noise from an image, the face image should be evaluated by clipping the face region from the acquired image. The recognized facial section must next be transformed into a black and white image [11] in order to be processed more efficiently. After that, each pixel location (i,*j*) into respective grayscale value is computed by weighted sum of red, green, and blue components in the face image. The RGB to gray scale image conversion process is done as follows in equation (1)

$$Gs(i, j) = 0.2989 * R(i, j) + 0.5870 * G(i, j) + 0.1140 * B(i, j). \tag{1}$$

Equation (1) assigns the calculated pixel value to the appropriate components in the facial image. After transforming the color image to grayscale, any distortion in the facial image has to be removed using the pretreatment procedures described above. The Perona-Malik dispersion technique[12] was adopted for this study becuase it removes noise from images while preserving edges, lines, and other important details. During the distortion eradication process, each pixel analyzes the collected face information in a diffusion-based manner. The pixels inspection produces the different blur patterns that are entangled with the image. After combining the image, the processing method is done to reduce the noise by widening the width of the image efficiently. Then, the acquired facial image is converted in terms of employing space consistent procedure to approximate the propagation process. During this procedure, the noisy pixel is substituted using image content, and the filter is selected depending on the pixel content. Assume the picture selection plane $\Omega \subset R2$, and the face gray scale photo group is denoted as $I(., t) : \Omega \rightarrow R$. After establishing the face gray scale picture, the relevant anisotropic dispersion [13] process is performed as shown in equation (2).

$$\frac{\partial I}{\partial t} = \operatorname{div}(c(x, y, t)\nabla I) = \nabla c.\nabla I + c(x, y, t)\,\Delta I, \tag{2}$$

The diffusion factor, indicated as c(x, y, t), is used to control the diffusion rate during the image gradient process. Equations (3) and (4) are used to estimate diffusion coefficient values.

$$c(\|\nabla I\|) = e^{-(\|\nabla I\|/K)^2} \tag{3}$$

$$c(\|\nabla I\|) = \frac{1}{1 + (\|\nabla I\|/k)^2} \tag{4}$$

In the equations above, k is utilized to manage the edge-related sensibility value, which is determined after successfully eliminating noise from a picture, with 96% accuracy in the noise-removing procedure. After reducing noise from the image, a face structure model was developed to classify threat-related facial images.

Consider the captured face (X) having so many points that is denoted as n and it is the $2n$ vectors, ie, $X = (x1y1, \ldots \ldots xnyn)^2$. The facial picture shape vector should be assigned the value {Xi}. According to the definition, the acquired image's shape matrices are represented as following. It depicts the face form model, which is used to produce vectors in face images that have multiple expressions, including neutral (NEU), mild, occupied, and enthusiastic (EX1,EX2,EX3). After building the physical model, the settings are used to extract new vectors from X. During this procedure, the trajectory points' dimensions must be decreased using the PCA approach [15]. The entering face image data set and the average value must be evaluated first, as shown in equation (5).

$$\mathrm{X} = \frac{1}{s}\sum_{i=1}^{s} X_i \tag{5}$$

The covariance matrix for the facemask image data set should then be determined, as shown in equation (6).

$$S = \frac{1}{s-1}\sum_{i=1}^{s}(X_i - X)\,(X_i - X)^T \tag{6}$$

To create an real training set for facial images, compute the eigen vector Pj and eigen value ƛj for data set S. Equation (7) uses the obtained values to estimate the training set for a particular image.

$$X \approx X^{-} + P_s\, b_s \tag{7}$$

where P_s is the face shape model variable and the image's eigenvector is denoted as b_s *in* equation (8) and (9).

$$b_s = P_s^T\,(X - X) \tag{8}$$

$$bi \in \{-3\sqrt{ƛj} + 3\sqrt{ƛj}\}\,. \tag{9}$$

After lowering the 3D of facemask points in the face, the figure of the face is formed using the following alteration on the expression image X points:

$$X = T\,(X^{-} + P_s\, b_s\,,\, x_c\; y_c\; s_x\; s_y \quad ,\Theta)\,. \tag{10}$$

In Equation (10), x_c, y_c is shown as an alteration of the input face image s_x , s_y is the image's scale value, while Ө rotates one of the facemask points in the face image. The produced shape model includes various facial traits that can be used for additional processing. The face traits are then extracted in order to identify and identify them.

Features Extraction: The Fisher linear discriminant analysis technique is used for obtaining facial traits in the third step of the work [16]. Both inside and between the scattering matrix, the technique calculates the characteristics. The following objective function is expressed in equation (11).

$$\mathrm{J(w)} = \frac{W^T S_B W}{W^T S_w W} \quad \ldots\ldots\ldots\ldots\ldots\ldots(11)$$

N_C represents number of instances in the class, is determined by the previously described equations. Equation (12) then estimates the total scatter value.

$$X^{-} = \quad \frac{1}{N_C}\sum_c N_c\, \mu_c \quad \ldots\ldots\ldots\ldots\ldots\ldots(12)$$

Generally, the throws are calculated as follows in equation (13)

$$S_T = S_W + S_B \quad \ldots\ldots\ldots\ldots\ldots....(13)$$

The appropriate Eigenvalues that were are removed from the dispersion points based on the image's calculated scatter points. The eigenvectors are then obtained by sorting the nonzero an eigenvalue in descending order. The features have been extracted by calculating the distance using the Euclidean method measure for each feature in the facial image after the eigenvalue and eigenvector have been determined. Following the application of the reduction function to the calculated distance value, the anticipated minimal distance values are handled as facial features and are taken from various facial regions. Entering facial points are matched with the appropriate feature using the characteristics extracted that are kept in the database.

Classification: Face recognition is the last phase of the job, which is completed with LAMSTAR's assistance [17, 18]. As was indicated in the previous part, IoT sensor cameras in smart cities constantly capture pictures of each individual, which are then sent to a management room adjacent. In order to reliably identify the people who pose an imminent danger, the faces of the people there are constantly compared to the database image. The safety and security of smart cities are enhanced by an efficient prediction process. The collection of retrieved picture characteristics that have been educated and acquired are kept in the relational database, as per the conversation. The aforementioned methods of feature extraction, face shape model development, and image noise removal are used for processing the fresh or incoming facial images. To identify the input features, the obtained facial characteristics are compared to the repository of features. LAMSTAR, another of the efficient DL techniques, performs the pairing procedure [19]. Numerous layers make up the network, and various filters are employed to eliminate noise during the step of matching. Furthermore, when compared with another classifier, the network's learning by yourself and motivational features enhance the matching procedure overall [20]. Additionally, the LAMSTAR technique is used in this work since the fastest learning algorithm and optimum link weights aid to maximize the face image detection process. Using the network's greater neuronal store and corresponding weight value, the LAMSTAR system verifies all of the faces in the training data set [21]. Then, the corresponding is done as follows in equation (14).

$$||x_i - w_i, m|| = \min || x_i - w_{i,k} || \ \forall k \in \langle l, l+p \rangle \quad \text{..................(14)}$$

x_i is the input features of the face, p is the number of nerve cell in the networks, and w is the weight that corresponds to vector of the stored facial features. The first characteristic in the list throughout the process of matchmaking is l, and the winning facial feature that matches is M. Network weight needs to be changed during the matching process to minimize comparing procedure divergence.

4. RESULTS AND DISCUSSION

When utilizing the technology, the data set needs to be developed in order to recognize the facial image in IoT smart cities. The list, which contains the criminal data and corresponding facial attributes, was previously generated by the system. The SC face picture data set, which was gathered from the interaction lab at Zagreb University's electrical engineering and computing department in Croatia, is used in this study. As a result, a computerized facial recognition device can identify faces in both static and dynamic settings. Based on the discussion, the sample SC face images are depicted in Figure 1. Here, the SC face picture data set is used to assess the method's effectiveness, and sufficient database information is given. The 680 × 556 pixel size of the recorded cctv photos is further decreased throughout the face detection and cropping procedures. Following the face recognition procedure, the image size will be cropped to a maximum of 100 × 75 pixels, depending on the crop range. Figure 1 shows an example of SC face photos based on the subject matter.

FIGURE 1. Sample SC face database images

TABLE 1. Facial feature learning network structure

Training Network	Number of input nodes	Number of hidden nodes in layer1	Number of hidden nodes in layer 2	Number of output nodes	Learning rate
CNN	16	12	10	1	0.0005

The accurate calculation as well as effective removal of weak attributes from the attribute list of $||x_i - w_i$,m $||$ aids in identifying the face traits from the characteristic list. Throughout the function comparison procedure, upgrading of $w_{i,m}$ (t+1) aids in minimizing the variation between calculated and estimated facial features. Additionally, choosing the appropriate αi learning factor lowers the ε_m during face picture classification.

TABLE 2. Face shape model accuracy

Accuracy	150	300	450	600	750	900
Frontal Pose	99.5	99.6	99.7	99.9	99.8	99.9
L1	99.3	99.2	99.4	99.6	99.7	99.8
L2	99.2	99.7	99.5	99.3	99.3	99.7
L3	99.5	99.8	99.6	99.5	99.4	99.8
L4	99.3	99.3	99.5	99.3	99.6	99.6
R1	99.5	99.5	99.7	99.4	99.5	99.7

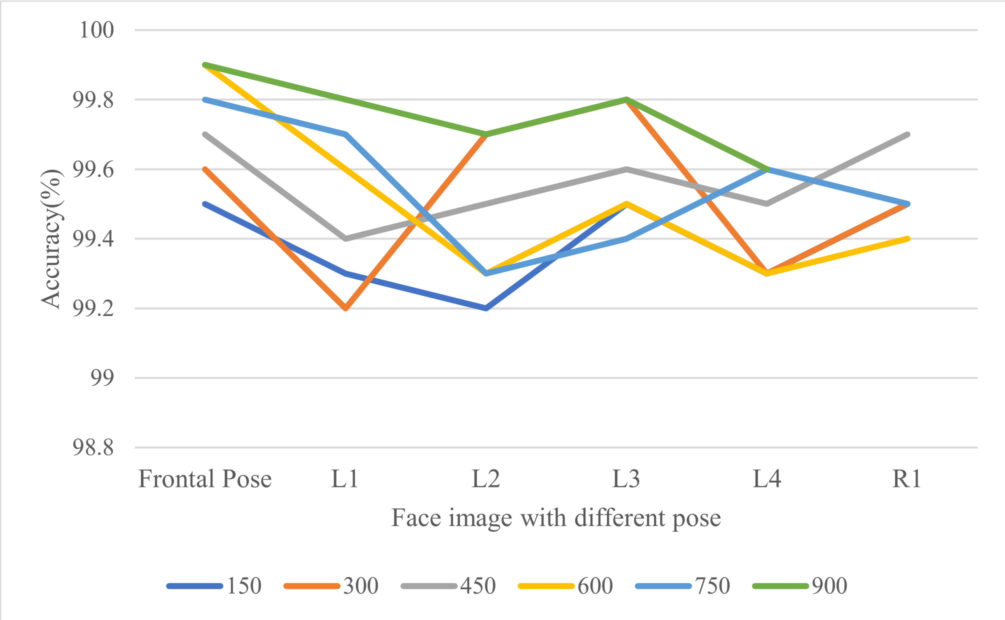

FIGURE 2. Graphical representation of accuracy based on face recognition

Table.2 and Figure.2 illustrated that the accuracy of introduced adaboost LAMSTAR classifier efficiency. The method successfully recognizes the incoming IoT sensor device-based face images with 99.9% of accuracy of different poses of the face. Compared to the conventional face recognition system, the efficient face recognition aids in the accurate prediction of criminal activity in smart cities.

5. CONCLUSION

The LAMSTAR-based facial identification method in the context of smart cities has been examined in this study. The IoT sensor camera is used to first record the face photos, and then it detects and crops the face region. The efficient diffusion approach is used to process the clipped face photos and remove noise from the images. The face form model is then created by identifying the shape vector, and the probability operators are used to efficiently derive attributes associated to the facial points. In order to enhance the learning process, the extracted features are processed by a convolution network, which learns the traits and stores them in a relational database. Using the LAMSTAR distance calculation technique, entering features are compared to the database image during the testing phase. The MATLAB program is used to create the system's accuracy, which guarantees 99.63% accuracy when identifying the image. Effective face image prediction contributes to smart city security and the early detection and elimination of criminal activity. With the aid of optimised methodologies that promote security in smart city environments, the face shape generating model and facial point detection procedure will be further enhanced in the future.

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