Kerbala Journal for Engineering Science

https://kjes.uokerbala.edu.iq/

A Survey on Multi-biometric Fusion Approaches

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Received: 24 November 2022; Revised: 19 June 2023; Accepted: 28 June 2023

ABSTRACT

The goal of biometrics is to reliably and robustly identify people based on their unique personal characteristics, primarily for security and authentication needs, but also to identify and track the users of more intelligent applications. Fingerprints, iris, palm prints, faces, and voices are common biometric modalities, but there are countless additional biometrics, such as stride, ear image, retina, DNA, and even behaviour. An automatic way to identify a person depends on just one (single-modal biometrics) or a mix of (multi-modal biometrics). A fusion of two or more images can create multi-modal biometrics, and the resulting fused image will be more secure. Various fusion methods are now available and may be categorised by the degree of information they combine. This paper discusses different fusion approaches implemented in multi-modal biometrics to identify human biometrics by extracting features and classifying images. It also describes the datasets that were used and the results and conclusions that were obtained.

Keywords:

Biometric Fusion; Deep Learning; Convolutional Neural Networks; Recognition System; Multi-Modal Biometric System; Level Fusion.

1. Introduction

The biometric system is a pattern recognition system that obtains biometric data from an individual's trait. A feature set will be extracted from this data for training the system, and then the system will be ready for personal identification or verification.

Figure 1 summarises the overall basic characteristics of the biometric recognition system. Here, a standard biometric recognition system does segmentation or detection, which entails extracting the modality of attention from the input and specifying some input data (e.g., an image, signal, or video). After that comes the pre-processing, which might involve things like data alignment, the elimination of noise, or data augmentation [1]. The pre-processed data is utilised to extract features, which a classifier uses to recognise biometrics. Associating an identification with the input data (such as through biometric identification) or establishing if two cases of the input data belong to the same identity are possible steps in the recognition process (e.g., biometric verification).

Figure 1. The general sequence of a face recognition system [2]**.**

Since traditional biometric recognition systems are uni-biometric and only use one biometric cue, they may have issues with missing information (such as an obscured face), bad data quality (such as a dry fingerprint), identity overlap (such as in the case of twins' face images), or restricted discriminability (e.g., hand geometry). Multiple biometric cues may be required to increase recognition accuracy [3].

This work aims to give a comprehensive overview of multi-modal biometric verification and the multi-modal biometric datasets available for research. This paper also includes a thorough examination of multi-modal biometric datasets and presents a variety of features. Images representative of several datasets were also provided when feasible. Using fusion schemes of characteristics, we sorted our output. The various fusion kinds are discussed in depth, along with their unique benefits and drawbacks. Additionally, the existing works' methodology, utilised databases, and accuracy outcomes demonstrate the extensive use of multi-modal biometric design.

The purpose of this review is to respond to the following questions about the literature:

Research Question 1: What are the number of fusion levels to merge multiple traits?

Research Question 2: What are the common fusion levels?

Research Question 3: What are the multi-modal biometrics' weaknesses?

Research Question 4: What challenges do multi-modal biometric systems face?

Research Question 5: What are the potential future directions for multi-modal biometric systems?

2. Multi-biometric systems

A multi-biometric system overcomes some of the limitations of a single-biometric system by intelligently combining data from many sources. Using numerous sources often enhances recognition performance and boosts system dependability since aggregate information is likely more discriminating to an individual than information gathered from a single source. The question of which types of information to fuse is resolved by looking at fusion at various points in the biometric identification process.

2.1 Biometric fusion

The performance of the multi-modal framework is greatly improved by the fusion approach [4]. An effective multi-modal biometric framework is built on the choice of an efficient fusion strategy to combine the pieces of evidence acquired from different cues [5]. The literature has five biometric fusion strategies: feature-level fusion, sensor-level fusion, score-level fusion, decision-level fusion, and rank-level fusion. It has been shown that the fusion of numerous cues is useful in a number of applications [6]. Different fusion levels of multiple biometric modalities have been investigated [7]. Fusion at the feature level and score level is likely to contribute to higher authentication accuracy since it provides increasingly satisfied achievable and practical data.

2.2 Levels of fusion

Biometrics Fusion (BF) can be implemented at varying stages throughout the biometric recognition pipeline and use various data sources. The multiple levels of fusion that can be applied to a biometric pipeline are shown in Figure 2, including the feature level, the sensor level, the score level, the decision level, and the rank level.

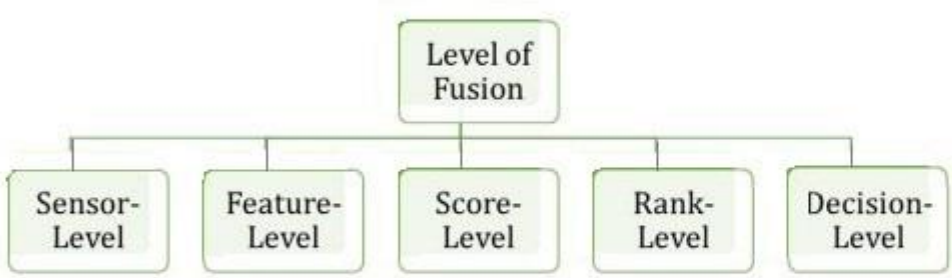

Figure 2. Fusion levels inside a multi-biometric system [8]

These levels correspond to the various modules of the biometric system (see Figure 1). Conversely, these degrees are viable for identification and verification systems, unlike rank-level fusion, which is typically only viable for identification systems.

Below, every one of these levels of fusion is described in more depth.

(i) Sensor-level fusion, where data is fused immediately after its acquisition, typically relates to multi-sample or multi-sensor methods. In other words, data fusion is done on the raw data itself before feature extraction [9]. This relates to a direct pixel-level collection of face photos taken from a camera in the case of a face recognition module. For instance, various poses like the right, frontal, or left profile can capture several faces. The samples can be joined using a mosaicing process to create a combined facial depiction. A direct fusion technique or adding pixels from two photos can also be used frequently [10].

(ii) Feature-level fusion combines various features from the same or separate input data. This could be equivalent to numerous feature sets for the same biometric type, such as various features from a hand- or a palm-print picture or structural and morphological features of a face image [11]. Additionally, it might match details taken from several modalities, such as photographs of the hands and faces [12]. Multi-biometric cryptosystems frequently employ these methods, which combine features from many biometric sources to increase security and privacy [11]. Additionally, they have been applied to index multi-modal biometric datasets[12]. Feature-level fusion merges various representations to create one representation for a specific person. For example, deep representation learning can be utilised to learn a shared representation of characteristics (features) taken from various modalities[11] [11].

(iii) Score level fusion refers to techniques that combine the match scores generated by various matches. Common fusion algorithms at this stage include max score fusion, mean score fusion, and min score fusion, respectively, where the maximum, mean, or minimum score among many matches is considered the final result[13] . In the literature, Dempster-Shafer theory and probabilistic methods like probability based on ratio score fusion have also been used [14]. Aside from that, in the situation of score-level fusion, Ding and Ross [8]explore several imputation strategies for handling missing or insufficient information. Due to the accessibility of accessing scores produced by commercial matches, this form of fusion is most frequently documented in the literature. The number of commercial matters does not offer simple access to features or, occasionally, even raw data.

(iv) Rank-level fusion is done after matching the input probe with the gallery set's templates or the database. The matcher frequently creates a ranked list of matched identities when performing an identification task comparing a specified probe image versus a gallery of photos. In the literature, regression models, Borda counts, and the top-rank method have been used to combine the rank lists from various matches [9]. Rank-level fusion is frequently considered efficient in settings with restricted access to features or matching scores.

(v) Decision-level fusion is accomplished according to algorithms that accomplish fusion at the decision level [15]. An example of a fusion algorithm most frequently used at the decision level is majority voting. The ultimate judgement is reached once n matches or classifiers combine their decisions and cast a majority vote. Because only the final judgements are available in black-box systems, decision-level fusion has the benefit of functioning well with them [16]. This is valid for many commercial applications where gaining access to features, scores, or rankings might not be possible.

3. Deep Learning

The system receives input from specified features in the traditional machine learning approach. In other words, only the most crucial elements are chosen or created. The engineer or programmer performs this manually, which means a software engineer would have to manually select the relevant features in a more traditional machine learning algorithm (manually choose features and a classifier) because traditional machine learning algorithms have a rather simple structure, such as linear regression or a decision tree. In contrast, deep learning algorithms require much less human intervention. The features are extracted automatically, and the algorithm learns from its errors. However, the best outcomes are not usually the result of doing this. Considering several phases and numerous methods for dealing with them, the best outcomes are not always achieved by manually selecting and developing features. This issue is resolved in deep learning by automatically extracting features from data using deep layers[17] . Figure 3 illustrates the critical distinction between ML and DL.

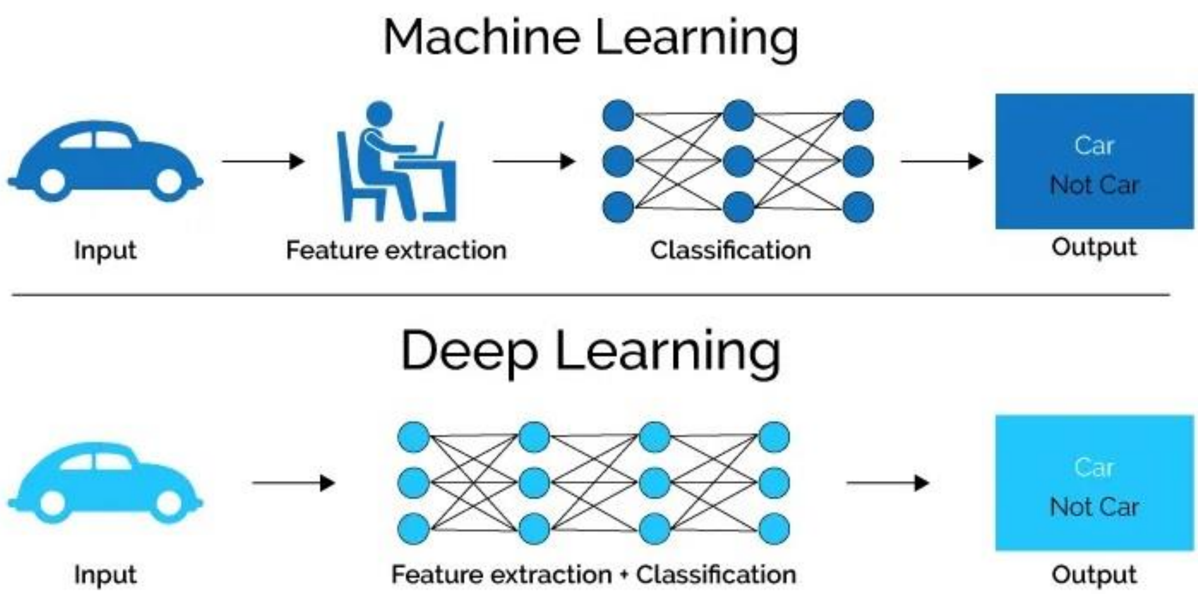

Figure 3. Basic distinctions between deep learning and machine learning [18]

3.1 Deep Learning Technique

Deep learning is a fascinating branch of machine learning techniques. Its main characteristic is the ability to create abstractions, which allows it to understand complex concepts from simpler ones. For instance, deep learning can learn concepts like people, cars, and cats in images by connecting groups of basic features like edges or corners. This procedure is carried out in consecutive layers, making the previously taught concepts more difficult. The following layer takes each output layer's input as a starting point for learning more advanced (complex) features.

3.2. Deep Neural Networks (DNN)

DNN is an ANN with several hidden layers in theory. One of the ANN structures that is frequently utilised for DNN is the MLP. It is nearly impossible to successfully train more than a few hidden layers since neural networks are made up of layers of coupled neurons. A network can have dozens or even millions of weights. Hence, the DNN needs many data to be fed into the training phases and incredibly long computation times[19][20].

Figure 4. represents a DNN architecture with five input nodes, four hidden layers with seven neurons, four output nodes and a simple neural network.

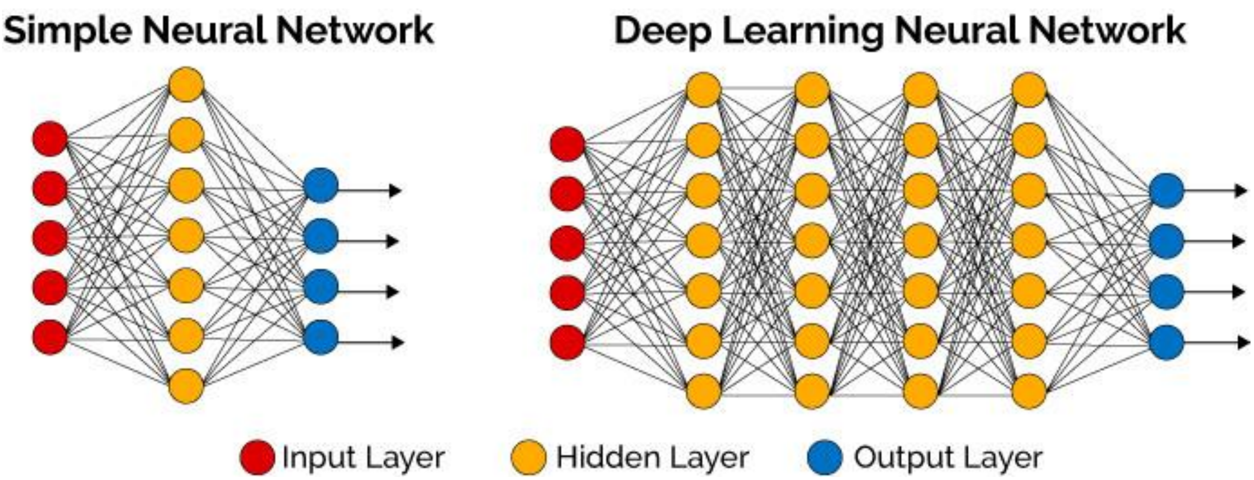

Figure 4. The architecture of Deep Neural Network [21]

3.3 Convolutional Neural Networks (CNN)

The CNN class of DNNs, dependent on MLP and backpropagation algorithms, is most frequently utilised in computer vision problems [19]. In contrast to standard MLPs, this one uses a combination of locally linked layers for feature extraction and several fully connected layers for classification. The most crucial qualities of CNN are its ability to learn local elements of the input image and its use of shared weights[21] .

3.4 CNN architecture

There are two main parts to the CNN architecture: A convolution tool that separates and identifies the various features of the image for analysis in a process called feature extraction. The network for feature extraction consists of many pairs of convolutional or pooling layers. A fully connected layer that utilises the output from the convolution process and predicts the class of the image based on the features extracted in previous stages. This CNN feature extraction model aims to reduce the number of features present in a dataset. It creates new features that summarise the existing features in the original set. There are many CNN layers, as shown in the CNN architecture diagram in Figure 5. Figure 5 depicts the conventional CNN architecture, which consists of three separate layers with groups of convolutional layers, subsampling (or pooling) layers, and fully connected layers.

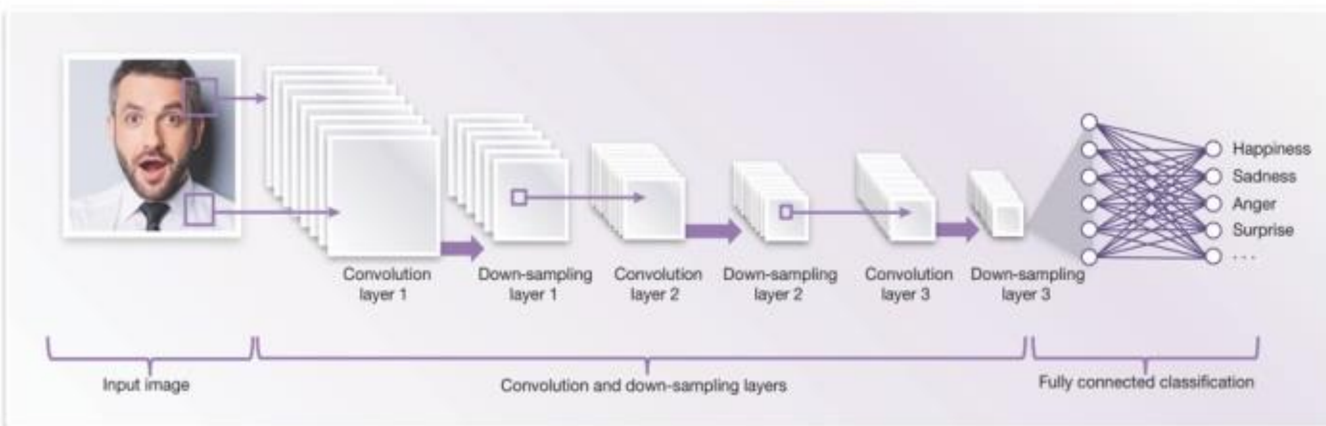

Figure 5. The architecture of Convolutional Neural Networks [22]

4. Literature Survey

One of the common and increasingly effective machine learning techniques used for feature selection, object classification, and object filtering processes is deep learning (DL) [23]. This section provides a survey of the most current developments in biometric fusion. Deep learning and artificial intelligence techniques in this field are particularly highlighted.

In Alay et al. [24], An innovative multi-modal biometric human recognition system is implemented that relies on a deep learning algorithm to identify people by their face, finger vein, and iris biometrics. The system's architecture is built on convolutional neural networks (CNNs), which classify images using a softmax classifier and feature extraction. Three CNN models—one for the face, one for the iris, and one for the finger vein—were integrated to create the system. The well-known pre-trained model VGG-16 was utilised in the construction of the CNN model, together with the Adam optimisation technique, and categorises cross-entropy as a loss function. Image enhancement and dropout techniques were used as some methods to prevent overfitting. Different fusion strategies combined the CNN models to investigate their effects on recognition performance. As a result, feature- and score-level fusion strategies were used. A multi-modal biometrics dataset, the SDUMLA-HMT dataset, was used in several experiments to assess the proposed system's performance empirically. The results showed that employing three biometric features produced better results than using two or one biometric traits in biometric identification systems. The results also demonstrated that our methodology greatly outperformed other state-of-the-art techniques, utilising different score-level fusion strategies to achieve an accuracy of 100% and a feature-level fusion strategy to get an accuracy of 99.39%.

Garg et al. [25] focus on the problem of multi-modal biometric fusion to increase recognition security. The paper uses speech, iris, and signature to create a revolutionary fusion. For each biometric, a separate classification mechanism is also presented. The fusion uses features taken out of each biometric during individual classification. For various biometrics, multiple feature extraction techniques are used. Their study uses Mel-frequency spectral coefficients for speech biometrics, Scale Invariant Feature Transform (SIFT) for signatures, and two-dimensional principle component analysis (2DPCA) for iris analysis. A genetic algorithm (GA) is used in this study's optimisation of the evaluated features. Artificial Neural Networks (ANN) are used for classification. The outcomes show that his suggested approach has a much greater accuracy range of 96–98%.

Sengar et al.[26], The proposed solution is based on multi-modal biometrics, in which palm print and fingerprint data are employed as a source of authentication. The "automated fingerprint identification system" (AFIS) often employs techniques based on specific information concentration. By using multi-modal biometrics, it is consistently possible to meet the goal of creating a secure, unique identification device. Palms and fingerprints rich in floor information achieve the highest level of accuracy. DNN's grounded distinction turns into a reasonable identification fee. The suggested method enhances noteworthy delivery and distinction accuracy within fresh factors. For example, ***(the suggested strategy grounded techniques to enhance distinction exactness involving frauds and genuine clientele in predicting FAR and FRR***). The outcomes show that his suggested approach has a much greater accuracy rate of 97%.

Vinothkanna et al.[27], They proposed employing a fuzzy vault to recognise palm prints, hand veins, and fingerprints using a multi-modal biometric technique. These pictures were initially pre-processed to remove any undesirable elements and to reduce noise levels **(*the nonlinear smoothing method used in the median filter is utilised to eliminate the blurring of edges and reduce the noise, and two primary morphological operations named erosion and dilation are applied to eliminate the obstacles and noise from the image*)**. The pre-processed image was then used for extracting the features. The chaff points and these extracted feature points were combined to create a single feature vector point. The fuzzy vault was created by combining the feature vector points with the points generated by the secret key. The authentication of a person is granted, and a secret key is created if their full feature vector matches that of the fuzzy vault. The fingerprint, hand vein, and palm print databases were used in the experiment, and the results showed that the suggested technique produces improved recognition with 98.5% accuracy.

Mahmoud et al. [28], A proposed multi-modal biometric identification technique to verify a person's identity using their iris and facial features. This methodology relies on various biometric methods integrating characteristics from the left and right iris to identify a person. A mechanism to identify people has been created and used by the writers. The face's features must be extracted using the rectangle histogram of oriented gradient (R-HOG). The work uses feature-level fusion, utilising a novel fusion technique that uses the suggested serial concatenation and the canonical correlation process. The recognition mechanism made use of a deep belief network. The suggested systems ' performance was confirmed and assessed through a series of experiments using the SDUMLA-HMT database. The results showed that the fusion time had decreased by roughly 34.5% compared to other outcomes. In addition, the suggested approach has produced results with a reduced equal error rate (EER) and up to 99% recognition accuracy.

xinman zhang et al. [29], Develop a reliable multi-modal biometric identification system for Android that uses voice and face recognition. To reduce this system's time and space complexity, a better LBP coding-based extracting of feature method is developed. They also offer an improved VAD technique to decrease the error ratio for the voice end, eliminate the bad voice segment, and increase algorithm performance in the low SNR case. They offer an adaptive fusion method to perform multi-modal biometric fusion authentication, which beats the drawbacks of uni-modal biometric authentication and significantly enhances the authentication performance, considering the Android-based smart terminal's hardware performance. The results of the experiments demonstrate the created authentication system's ability to successfully deploy identity identification in various scenarios and execute management tasks with high-security applications.

Abderrahmane et al. [30] proposed a new method based on the weighted quasi-arithmetic mean (WQAM) for score-level fusion. In particular, WQAMs are calculated using various trigonometric functions. The weighted mean and quasi-arithmetic mean characteristics are both included in the suggested fusion method. Furthermore, there is no learning process necessary. Results of experiments using the publicly available NIST-BSSR1 Multi-modal, NIST-BSSR1 Fingerprint, and NIST-BSSR1 Face data sets

Rane and Bhadade [31] proposes a multi-modal, heterogeneous biometric authentication system that uses a matching score fusion technique depending on the t-norm. Developing a multi-modal recognition system based on two qualities uses biometric traits like the face and palm print. First, facial and palm print characteristics are extracted, matching scores for each trait are determined using correlation coefficients, and matching scores are combined using the t-norm depending on score level fusion. Face databases like FERET, FRGC, Face 94, Face 95, and Face 96, and palm-print databases like IITD are used for algorithm training and testing. The experiments' results indicate that the suggested algorithm significantly enhances a biometric recognition system's accuracy, providing a "genuine acceptance rate" (GAR) of 99.7% at a "false acceptance rate" (FAR) of 0.1% and a GAR of 99.2% at a FAR of 0.01%. Compared to previous work, the suggested approach offers 0.53% more accuracy at FARs of 0.1% and 2.77% more at FARs of 0.01%.

Srivastava [32], A practical security interrogation of the multi-modal biometric cryptography system using the individual finger impression, retina, and finger vein has also been conducted. These biometrics provide a remarkable improvement in performance in a multi-modal biometric cryptography system using RSA and the DNN order approach. The structure makes use of the score-level combination strategy. This hypothesis comprises a proposed framework for confirmation based on the retina, individual finger impressions, and recognition of finger veins. The proposed framework expands the presentation of a retinal, finger vein, and unique finger impression acknowledgement verification by creating a new technique at the score level combination. DNN is used to perform orders, RSA is utilised for encryption, and SIFT computation is used to complete the highlight extraction process. Compared to uni-modal biometric frameworks, the total performance of the multi-modal framework has improved by 98.9% with GAR, 98.5% with accuracy, and 0.05% with FAR.

Devi and Rao [33] developed three decision-level fusion systems, Global Decision Fusion (GDF), Local Decision Fusion (LDF), and Local-Global Decision Fusion (LGDF), by utilising global and local information. The suggested method employs low- and high-frequency wavelet sub-bands to retrieve this information. Following the independent classification of the sub-bands using the nearest neighbour classifier, the resulting classes are fused using a balanced qualified majority. In comparison to uni-modal GDF, LDF, and two low-frequency sub-band-based approaches, the suggested LDF and GDF methods demonstrate a maximum increase in the average recognition rates of 9.4%, 11%, 10.6%, and 11.5%, respectively. Furthermore, the average recognition rate of 6.75% of the suggested LGDF approach is higher than that of feature-score hybrid fusion.

Iloanusi and Ejiogu [34], They suggest a convolutional neural network architecture based on deep learning for classifying gender from fingerprints of each of the five different finger types and compare the results of trained models. We show that the classification of gender using fingerprints from fused combinations of the five right-hand finger types can increase performance. Gender classification has traditionally been done using the index finger. His findings, however, indicate that some finger kinds more accurately define one gender than the other. Researchers take advantage of the diversity among fingerprint types by fusing together an odd number of models trained on various fingerprints. The best fusion model's male, female, and overall classification accuracy rates are 94.7%, 88.0%, and 91.3%, respectively. , giving improvements of 31.02%, 7.82%, and 18.72%, respectively.

Zhou et al.[35] proposed a novel model using a hybrid fusion method for a multi-modal biometric system. A unique weighting vote approach and an enhanced feature fusion algorithm are both included in this hybrid fusion model. It uses score distribution data to guide decision-making while capturing canonical traits with a multi-set structure. The system was tested using PolyU, CASIA, and SDU databases, which offered superior precision and robustness over earlier studies. According to experimental findings, the suggested method beat alternative fusion procedures in multi-modal biometric systems with an average accuracy of 99.33%.

Chang et al. [4], Multi-biometric cryptosystems have been proposed to increase security and boost recognition capabilities. They combine numerous biometric traits using a singular cryptosystem or several independently accessible cryptosystems. An attack may compromise the entire system's security on one of the related cryptosystems. Their study introduced a strategy called BIOFUSE for multi-biometric fusion that collects fuzzy commitments and fuzzy vaults using a scheme for format-preserving encryption. BIOFUSE makes it improbable for an attacker to get unauthorised access to the system without impersonating the genuine user's biometric inputs at the same instant. They provide the four simplest methods for building BIOFUSE; however, only one, SBIOFUSE (S3), was discovered to be a secure method. On several databases, they compare the suggested scheme's recognition performance to multi-biometric cryptosystems already in use. The findings on a virtual IITD-DB1 database reveal a 0:98 true match rate at a 0:01 false match rate, demonstrating their suggested work produces high recognition performance while offering increased security.

Wajid et al. [36] suggested a multi-modal biometric method based on a single palm and fingerprint. The experimental evolution used the UPEK fingerprint and IITD palm-print databases. The suggested system obtained FAR of 2.0%, FRR of 2.25%, and TSR of 98.75%, with a total matching time of 1.90 seconds.

Yadav [37], a new multi-modal human identification model based on a deep learning algorithm is proposed using the biometric modalities of iris, fingerprint, and handwritten signatures. The system's architecture is built on 'convolutional neural networks (CNNs), which extract the features and use the softmax classifier to categorise the photos. Three CNN models—one for the fingerprint, one for the iris, and one for the handwritten signature—are integrated to create the system. Categorical cross-entropy was utilised as a loss function, and VGG-32 and the Adam optimisation approach were used to develop the CNN model. Specific methods, like photo augmentation and dropout techniques, were used to prevent over-fittings. Different fusion strategies combined the CNN models to explore their effects on recognition performance. As a result, feature- and score-level fusion strategies were used. The multi-modal biometrics dataset SDUMLA-HMT was used to conduct many tests to evaluate the performance of the suggested system. The acquired results showed that employing three biometric qualities produced better results than using one or two biometric types in biometric identification systems. By reaching an accuracy of 99.11 percent with the feature-level fusion technique and 99.51% with a different approach to score-level fusion, the results further demonstrate that our methodology easily surpassed previous state-of-the-art methods.

Kamlaskar and Abhyankar [38] proposed feature level fusion using "canonical correlation analysis" (CCA) to combine the feature sets of a person's iris and fingerprint. This approach is distinctive in that it pulls maximally correlated features as useful discriminant information from the feature sets of both modalities. The fundamental relationship between two feature spaces may thus be examined using CCA, which produces more potent feature vectors by eliminating extraneous data. They demonstrate that effective multi-modal recognition can be achieved with a significantly reduced feature size, simpler computations, and less than one-second recognition times by employing CCA-based joint feature fusion and optimisation. Thumb fingerprints from both hands left and right iris, and the multi-modal dataset ' SDUMLA-HMT ' are taken into account in this experiment to evaluate the effectiveness of the proposed system. We demonstrate that the performance of the suggested technique greatly beats that of the unimodal system in terms of equal error rate (EER). Additionally, they show that CCA-based feature fusion outperforms match-score level fusion. Additionally, a study of the correlation between images of the left and right fingerprints (EER of 0.1050%) and the left and right iris (EER of 1.4286%) is presented to take into account the impact of laterality and feature dominance of the selected modalities for a trustworthy multi-modal biometric system.

Kumar et al.[39] proposed fusing features of the face and fingerprint recognition system as an "improved biometric fusion system" (IBFS), which results in increased performance. Integrating multi-biometric attributes enhances recognition performance, which lowers unauthorised access. This work introduces an IBFS that includes the ' improved face recognition system' (IFRS) and the improved fingerprint recognition system' (IFPRS) for authentication. For IFPRS and IFRS, the whale optimisation algorithm is combined with the details feature and "maximally stable external regions" (MSER). The planned IBFS is trained using a net pattern model classification approach. The IBFS model is trained using pattern networks that depend on a processed data set and SVM to improve classification accuracy. The suggested fusion system's average true positive rate and accuracy were 99.8% and 99.6%, respectively.

Vijayakumar et al.[40] constructed a multi-modal biometric user identification model for use with current technologies. The system performs feature extraction using the CNN deep learning method to accurately and error-freely identify an individual. The face, iris, palm print, and finger vein were used to identify the subject, along with two different ways of scoring. To our knowledge, this is the first research that examines the application of deep learning models to a multi-modal biometric model that includes palm prints. Additionally, no work has been done using palm prints on a multi-modal biometric authentication system. Regarding more research, Instead of using a pre-trained model, this research intends to create hybrid deep-learning classification approaches from scratch that are appropriate for each character. Combining a convolutional neural network (CNN) with a finger vein support vector machine (SVM), for example, improves the accuracy of palm-print image recognition. In most cases, the SVM provides accurate image classifications. More than just DNA and signatures, this study uses deep learning algorithms to look into other identifiers like hand shapes. The recommended model's use of multi-level fusion processes and a variety of multi-modal datasets would also be interesting for expanding the scope of testing.

Arjun and Prakash et al.[41] presented a hybrid model created by fusing multiple levels of multi-modal biometrics. In addition to two levels of fusion (decision level and feature level), this model took into account the two biometric modalities of the face and finger vein. This study employs five classifiers for majority voting: K-Nearest Neighbour, Ensemble Discriminant, Ensemble Subspace K-Nearest Neighbour (ESKNN), Linear Discriminant, and SVM. In this work, we up-sample the image using bilinear interpolation methods, resulting in images with a wealth of detail. The recognition rate is higher when using the proposed model compared to unimodal biometric systems.

Channegowda et al. [42], we designed multi-modal biometric models to increase the accuracy of recognising a person. This approach makes use of a combination of physiological and behavioural biometric traits. The qualities of signature biometrics and fingerprints are integrated to create a multi-modal recognition system. Biometric traits derive histograms of oriented gradient (HOG) features, which are then fused at two different levels. At multilayer levels, the characteristics of fingerprints and signatures are combined using the concatenation, min, max, sum, and product rules. Deep-learning neural network models are then trained using these features. The outcomes of the proposed study are assessed by various hidden layers and hidden neurons using a deep learning classifier and multi-level feature fusion for multi-modal biometrics. Experiments were conducted on the MCYT and SDUMLA-HMT signature biometric recognition datasets, and positive results were obtained.

(Sarangi et al.[43] suggested that it addresses the drawbacks of ear biometrics and boosts the total recognition rate. It is based on the profile of the face and ear. First, two effective local feature descriptors, local directional patterns (LDP) and local phase quantisation (LPQ), are combined to describe the ear and profile face modalities individually. A high-dimensional feature vector is created by fusing these histogram-based local descriptors, which maintain complementary information in the frequency and spatial domains. Each feature vector is individually subjected to the PCA and the z-score normalisation procedure, and the resulting reduced feature vectors are aggregated at the feature level. To generate more discriminatory and nonlinear characteristics for identifying people using a KNN classifier, the kernel discriminative common vector (KDCV) technique is finally utilised over the collected feature set. With the help of deep features extracted from three well-known pre-trained CNN models, namely AlexNet, GoogleNet, and VGG16, the effectiveness of the proposed model has been confirmed. Experimental results on two benchmark datasets unmistakably demonstrate that the suggested strategy outperforms individual modalities and other cutting-edge techniques in terms of performance.

Purohit and Ajmera [44], they proposed an efficient feature-level fusion technique for a multi-modal biometric recognition system. They considered merging multi-modal biometric features, including a fingerprint, ear, and palm. Four main processes, such as pre-processing, feature extraction, better feature level fusion, and recognition, were carried out in our suggested methodology. They employed a modified region-growing method to extract form features, and for extracting texture features, they used the HMSB operator. Further used is the optimisation strategy to choose the pertinent features. They applied the OGWO+LQ algorithm to choose the best feature. Ultimately, they suggested recognition using the multi-kernel support vector machine (MKSVM) technique.

Jaswal and Poonia [45] suggested a multi-modal biometric approach to be useful for identifying the culprits in cases of physical assault or kidnapping and establishing supporting scientific proof when no face or fingerprint information is provided in images. Data preparation, the first stage of our investigation, involved extracting the region of interest from finger knuckle and palm images. To start, we normalise the recognised circular finger knuckle or palm before using a line ordinal pattern (LOP) based on an encoding approach for texture enrichment to reduce the impact of non-uniform lighting. When extracted over the suggested LOP encoding, the non-decimated quaternion wavelet offers denser feature representation at many scales and orientations and boosts the discrimination ability of line and ridge features. To the best of our knowledge, the dominant palm and knuckle characteristics have been chosen for classification in this first effort using a mix of the backtracking search algorithm and 2D2 LDA. The classifiers' output for the two modalities is collected using the Borda count method at the unsupervised rank level fusion rule, which results in an improvement in recognition and verification performance with values of 1,262 m (speed), 3.52 (discriminative index), 0.26% (equal error rate), 100% (correct recognition rate), and 100% (correct recognition rate).

Tharewal et al.[46]This project intends to develop fusion deep-learning classification algorithms from scratch that are suitable for each character instead of using a pre-trained model. For instance, combining CNN with a finger vein (SVM) support vector machine increases accuracy for palm-print image recognition. In general, the SVM does a good job of classifying the photos. Additionally, a larger range of identification features, like DNA, signatures, and hand shapes, are investigated in this research using deep learning algorithms. It would also be intriguing to apply the suggested model with its many level fusion procedures and diverse multi-modal datasets to widen the scope of testing. Finally, using score-level fusion, the three-dimensional ear and face are combined. For the 3D ear and 3D face datasets, simulations are run on the Face Recognition Challenge databases and the ' Notre Dame University Collection F databases. According to experimental findings, the proposed model uses the proposed score-level fusion to reach an accuracy of 99.25%. Comparative studies reveal that the suggested technique outperforms existing state-of-the-art biometric algorithms in terms of accuracy.

Mohammed et al.[47], The author delves deeply into the power of multi-biometric fusion for individual identification. The Dis-Eigen algorithm is a brand-new feature-level algorithm that is suggested. Here, a feature-fusion architecture is suggested for improving accuracy when using various biometrics to identify a person. The framework, which directs multi-biometric fusion implementations at the feature level for identifying individuals, thus serves as the foundation for the new multi-biometric system. This framework used the faces and fingerprints of 20 people, each represented by 160 photos. Experimental results of the suggested methodology reveal a feature-level fusion multi-biometric individual detection rate of 93.70 percent.

Joseph et al. [48]develops a multi-modal biometric system based on face and fingerprint identification. The multi-modal biometric person recognition system is first created using the ORB (Oriented Fast and Rotated Brief) algorithm and the Convolutional Neural Network (CNN). The following step is the matching score-level fusion based on the weighted sum rule of two features. The verification procedure matches if a fusion score is higher than the predetermined threshold t. The algorithm is thoroughly examined using datasets from the database for the UCI Repository of Machine Learning, including one genuine dataset with cutting-edge techniques. In the person-recognition system, the suggested strategy yields an encouraging result.

Banati et al.[49] uses a multi-modal biometric framework that fuses face, palm print, and fingerprint biometric modalities at the score level. The scores are first derived from distinct biometric features to create the final fusion score. This rating is used to verify people's identities. The feature vectors of various photos are computed to produce the score. Individual feature vectors derived from the face, palm-print, and fingerprint are pre-processed and then normalised to create a specific template for matching. Scale-invariant feature transformation (SIFT) and accelerated robust features (SURF) are two techniques combined in the authentication process. The scores are first derived from distinct biometric features to create the final fusion score. This rating is used to verify people's identities. The feature vectors of various photos are computed to produce the score. To create a specific template for matching, the individual feature vectors derived from the face, palm print, and fingerprint are pre-processed and then normalised. Scale-invariant feature transformation (SIFT) and accelerated robust features (SURF) are two techniques combined in the authentication process. Before applying SURF to the feature descriptors produced by SIFT, the scores are first computed using SIFT. Three fusion rules, MIN, MAX, and SUM are utilised in this fusion. The scores are generated after the rules are put into effect. Human identification is verified using the highest score out of the three. This work's 95.08% authentication rate is higher than the individual SIFT and SURF rates and is an improvement.

Table 1: A summary of the literature reviews above.

id	Authors	Biometric Traits used	Fusion Approach	used algorithms	datasets	Performance Metrics
1	(Alay and Al-Baity 2020)	Iris, Face, and Finger Vein	a feature level fusion, different methods of score level fusion	CNN model (VGG-32), softmax classifier	SDUMLA-HMT	Accuracy =99.39% Accuracy =100%
2	(GARG, ARORA, and GUPTA 2020)	iris, speech, and signature	a feature-level fusion	2-Dimensional Principle Component Analysis (2DPCA) ,Scale Invariant Feature Transform (SIFT) ,ANN classifier	a mixture of standard and real-time data set.	Accuracy =96-98%
3	(S. Sengar, Hariharan, and Rajkumar 2020)	Fingerprint & Palm-Print	a feature level fusion	DNN	Chimeric Dataset	FRR = 0.02%, FAR = 1.3%, Accuracy = 97%
4	(Vinothkanna * and Wahi 2020)	Fingerprint, Palm- Print & Hand-vein	a feature level fusion	fuzzy vault	CASIA Datasets	Accuracy = 98.5%,GAR = 0.85
5	(Mahmoud, Selim, and Muhi 2020)	Iris & Face	a feature level fusion	(R-HOG)	SDUMLA-HMT Database	Accuracy = 99%
6	(xinman zhang et al. 2020)	Face & Voice	score level fusion	(LBP) ,(VAD)	Own Dataset	Accuracy = 98%
7	(Abderrahmane et al. 2020)	Fingerprint & Face	score level fusion	WQAM	NISTBSSR1 Multimodal, NISTBSSR1 Fingerprint & NISTBSSR1 Face	GAR = 91.60%, EER = 2.78%
8	(Rane and Bhadade 2020)	Palm-print and face	score level fusion	ROI	Face 94, Face 95, Face 96, FERET, FRGC & IITD	GAR = 99.7%
9	(Srivastava 2020)	Retina, finger-vein and fingerprint	score level fusion	RSA and DNN	Chimeric Datasets	Accuracy = 91%, FAR = 89%, GAR = 95%

10	(Devi and Rao 2020)	Palmprint & Face	decision level fusion	LDF and GDF ,DWT	Chimeric Database	RR = 98.12%
11	(Iloanusi and Ejiogu 2020)	Multiple Fingerprints	decision level fusion	CNN	Own Datase	Accuracy = 94.7%
12	(Zhou et al. 2020)	Finger-vein, Iris & Palm-vein	(features, scores & decision) level fusion	DCA	CASIA, PolyU & SDU	Accuracy = 99.33%
13	(Chang et al. 2020)	iris - fngerprint	biocryptosystem level fusion	S-BIOFUSE	virtual IITD-DB1 database	0:98 true match rate at 0:01 false
14	(Wajid et al. 2020)	Palm and Fingerprint	score level fusion	ROI	IITD touchless palm-print and UPEK fingerprint	FAR=2.0%, FRR=2.25% and TSR=98.75%
15	(Yadav 2021)	Iris, fingerprint and written signature	a feature level fusion , different methods of score level fusion	CNN model (VGG-32), softmax classifier	SDUMLA-HMT	Accuracy =99.11% Accuracy =99.51%
16	(Kamlaskar and Abhyankar 2021)	iris - fngerprint	a feature level fusion	canonical correlation analysis (CCA)	SDUMLA-HMT	Right Iris and Right Fingerprint images (EER of 0.2812%) and b) Right Iris and Left Fingerprint images (EER of 0.1050%),
17	(Kumar, Bhushan, and Jangra 2021a)	face and fingerprint	a feature level fusion	Whale optimisation (IFPRS) ,(IFRS)	FVC fingerprint database and face images were collected from Georgia Tech face database	Accuracy =99.6%
18	(Vijayakumar 2021)	iris, face, finger vein, and palm print	a feature level fusion score level fusion	CNN	USM and SDUMLA-HMT	Accuracy =94%

19	(Arjun and Prakash 2021)	face - finger vein	decision Level fusion a feature level fusion	ESD ,KNN ,LD ,SVM ,ESKNN	face data sets from AT&T and finger vein data sets from SDUMLA-HMT	Accuracy =95%
20	(Channegowda a. b. and Prakash 2021)	Fingerprint - Signature	multi-level feature fusion	CNN	fingerprint from SDUMLA-HMT and signature from MCYT	Accuracy =93.33%
21	(Sarangi et al. 2021)	ear - profile face	a feature level fusion	CNN (AlexNet, VGG16 and GoogleNet)	side face images of the collection E (UND-E) and collection J2 (UND-J2) databases.	Accuracy =99.05
22	(Purohit and Ajmera 2021)	Fingerprint, Ear, and Palm-Print	a feature level fusion	(MKSVM)	ITD Ear-Print, CASIA Palm-Print, CASIAFingerprintV5	Sensitivity = 0.91667%, Specificity = 0.91667, Accuracy = 0.91667
23	(Jaswal and Poonia 2021)	Palm-Print & FingerKnuckle-Print	rank level fusion	f backtracking search algorithm and 2D2 LDA , (LOP)	CASIA Palm print, IIT Delhi Palm print and PolyU FKP	CRR = 100%, EER = 0.26, DI = 3.52
24	(Tharewal et al. 2022)	(3D) face - ear	score-level fusion model	(PCA) for 3D face recognition (ICP) for 3D ear recognition	FRGC database for 3D face and UND collection F database for 3D ear.	Accuracy =99.25
25	(Mohammed et al. 2022)	face - fingerprint	a feature level fusion	Dis-Eigen a	(AUMI)	Accuracy =93.7%
26	(Joseph et al. 2022)	face and fingerprint	score level fusion	(CNN) and ORB	UCI machine learning repository database	Accuracy =96%
27	(Srivastava 2022)	Face, Finger & Palm-print	score level fusion	SIFT , SVM	IIT-D & Poly-U Data set	Accuracy = 95.48%

5. Conclusion

The goal of this paper is to distribute the research done in the biometric fusion field for authentication. The study begins with discussing different bottlenecks that uni-modal biometric systems may have, focusing on information scarcity, intra-class differences, universality, and acceptability. The scientific community has focused on the amalgamation of multiple biometric traits as a means of overcoming these constraints. This combination reduces the drawbacks of employing a single biometric modality while increasing the chance of a more secure authentication system. The paper discusses several recent papers regarding the methodology, modalities and databases used and results in recognising accuracies and EERs.

This article focuses on the type of fusion because it appears to be the classification most interesting to newcomers and readers. This classification is crucial since it directly affects the accuracy that is attained. Score-level and feature-level fusion is the most general technique, as can be inferred from the thorough study provided in this work.

On the other hand, feature-level fusion is hampered by the features uncorrelated nature and increasing dimensionality. However, sensor-level fusion cannot be considered a fusion strategy that is universally accepted because it is frequently exceedingly challenging to fuse the relevant modalities at the sensor level. decision-level fusion, which is carried out after various classifiers have reached a decision, is very sensitive to the accuracy of each classifier, which may result in inaccurate choices. Additionally, it may be deduced that most literature attempts to fuse the modalities produced by the same portion or region of the body. For instance, there have been various attempts to integrate the capabilities of hand geometry, fingerprint, fingernail, palm print, and palm vein. Similarly, there is much interest in merging metrics from the iris, face, periocular, and ocular images. However, intriguing effects might be attained if modalities from two separate bodily locations are combined.

It is crucial to analyse these discoveries and advancements for future research due to the growing advances in artificial intelligence in several spheres of life. It was required to review the recently published studies in this field because biometric fusion using deep learning techniques is one of the study fields that has been active for the past ten years. The value of biometric fusion can be employed in a wide range of contexts where biometric authentication is necessary and not just important for certain applications. We browsed the most current studies on biometric fusion that have been published. Our work concluded that utilising deep learning techniques has been the most effective method for fusing biometric data. More research is needed to compare the various deep-learning neural network structures utilised in this field.

References

[1] A. Kamboj, R. Rani, and A. Nigam, "A comprehensive survey and deep learning-based approach for human recognition using ear biometric," *Visual Computer*. 2021. doi: 10.1007/s00371-021-02119-0.

[2] K. Nandakumar, A. Ross, and A. K. Jain, "Biometric_fusion_Does_modeling_correlati.pdf." 2009.

[3] K. Ricanek, P. N. Belhumeur, and T. E. Boult, "must be obtained for all other uses , in any current or future media , including Fusing with Context : a Bayesian Approach to Combining Descriptive Attributes." 2011.

[4] D. Chang, S. Garg, M. Ghosh, and M. Hasan, "BIOFUSE: A framework for multi-biometric fusion on biocryptosystem level.pdf." 2020.

[5] K. Saeed *et al.*, "A Novel Extension for e-Safety Initiative Based on Developed Fusion of Biometric Traits.pdf." 2020.

[6] L. Di Martino, G. Garella, J. Preciozzi, A. Fernandez, F. Lecumberry, and R. G. von Gioi, "An a-contrario Biometric Fusion Approach .pdf." 2020.

[7] S. K. Choudhary and A. K. Naik, "Multimodal biometric authentication with secured templates – A review," *Proceedings of the International Conference on Trends in Electronics and Informatics, ICOEI 2019*, vol. 2019-April. pp. 1062–1069, 2019. doi: 10.1109/icoei.2019.8862563.

[8] M. Singh, R. Singh, and A. Ross, "A comprehensive overview of biometric fusion.pdf." 2019.

[9] S. Bharadwaj, M. Vatsa, and R. Singh, "Aiding face recognition with social context association rule based re-ranking," *IJCB 2014 - 2014 IEEE/IAPR International Joint Conference on Biometrics*. 2014. doi: 10.1109/BTAS.2014.6996266.

[10] R. Singh, M. Vatsa, A. Ross, and A. Noore, "A Mosaicing Scheme for Pose-Invariant Face Recognition.pdf." 2007.

[11] A. Ross, S. Shah, and J. Shah, "Image versus feature mosaicing: a case study in fingerprints.pdf." 2006.

[12] A. Ross, R. Govindarajan, and Arun, "Feature level fusion of hand and face biometrics.pdf." 2005.

[13] D. Yi, Z. Lei, and S. Z. Li, "Shared representation learning for heterogenous face recognition," *2015 11th IEEE Int. Conf. Work. Autom. Face Gesture Recognition, FG 2015*, no. April, 2015, doi: 10.1109/FG.2015.7163093.

[14] N. Poh, J. Kittler, and T. Bourlai, "Improving biometric device interoperability by likelihood ratio-based quality dependent score normalization," *IEEE Conference on Biometrics: Theory, Applications and Systems, BTAS'07*. 2007. doi: 10.1109/BTAS.2007.4401964.

[15] K. Veeramachaneni, L. Osadciw, A. Ross, and N. Srinivas, "Decision-level fusion strategies for correlated biometric classifiers," *2008 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops*. 2008. doi:

10.1109/CVPRW.2008.4563104.

[16] A. J. M. Indovina, U. Uludag, R. Snelick, A. Mink, "Multimodal Biometric Authentication Methods: A COTS Approach M.pdf." 2003.

[17] F. Shaheen, B. Verma, and M. Asafuddoula, ""Impact of Automatic Feature Extraction in Deep Learning Architecture," *Int. Conf. Digit. Image Comput. Tech. Appl.,* pp. 1–8, 2016, doi: 10.1109/DICTA.2016.7797053.

[18] J. Schmidhuber, "Deep Learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85–117, 2015, doi: 10.1016/j.neunet.2014.09.003.

[19] X. SERRA, "Face recognition using Deep Learning," *Polytech. Univ. Catalonia,* 2017.

[20] and Y. W. T. G. E. Hinton, S. Osindero, "A fast learning algorithm for deep belief nets," *Neural Comput.*, 2006.

[21] L. D. and S. Dongmei, "Contactless palmprint recognition based on convolutional neural network," *IEEE 13th Int. Conf. Signal Process.*, 2016.

[22] L. A. et Al Alzubaidi, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J. Big Data, vol. 8, no. 1, Dec.*, 2021, doi: 10.1186/s40537-021-00444-8.

[23] M. Paliwal and U. A. Kumar, "Neural networks and statistical techniques: A review of applications," *Expert Systems with Applications*, vol. 36, no. 1. pp. 2–17, 2009. doi: 10.1016/j.eswa.2007.10.005.

[24] N. Alay and H. H. Al-Baity, "Deep Learning Approach for Multimodal Biometric Recognition System Based on Fusion of Iris, Face, and Finger Vein Traits," *Sensors*, vol. 20, no. 19, p. 5523, Sep. 2020, doi: 10.3390/s20195523.

[25] M. GARG, A. S. ARORA, and S. GUPTA, "A NOVEL FEATURE BIOMETRIC FUSION APPROACH FOR IRIS, SPEECH AND SIGNATURE MAMTA.Pdf." 2020.

[26] S. Sengar, U. Hariharan, and K. Rajkumar, "Multimodal Biometric Authentication System using Deep Learning Method Sandeep.pdf." 2020.

[27] R. Vinothkanna* and A. Wahi, "A multimodal biometric approach for the recognition of finger print, palm print and hand vein using fuzzy vault.pdf." 2020, 2020.

[28] R. O. Mahmoud, M. M. Selim, and O. A. Muhi, "Fusion Time Reduction of a Feature Level Based Multimodal Biometric Authentication.pdf." 2020.

[29] xinman zhang, C. Dongxu, P. Jia, D. Yixuan, and X. Xuand, "An Efficient Android-Based Multimodal Biometric Authentication System with Face and Voice.pdf." 2020.

[30] H. Abderrahmane, G. Noubeil, Z. Lahcene, Z. Akhtar, and D. Dasgupta, "Weighted quasi-arithmetic mean based score level.pdf." 2020.

[31] M. E. Rane and U. S. Bhadade, "Multimodal score level fusion for recognition using face and palmprint," *International Journal of Electrical Engineering Education*. 2020. doi: 10.1177/0020720920929662.

[32] R. Srivastava, “Score-Level Multimodal Biometric Authentication of Humans Using Retina, Fingerprint, and Fingervein,” *International Journal of Applied Evolutionary Computation*, vol. 11, no. 3. pp. 20–30, 2020. doi: 10.4018/ijaec.2020070102.

[33] D. V. R. Devi and K. N. Rao, “Decision level fusion schemes for a Multimodal Biometric System using local and global wavelet features.pdf.” 2020.

[34] O. N. Iloanusi and U. C. Ejiogu, “Gender classification from fused multi-fingerprint types,” *Information Security Journal*, vol. 29, no. 5. pp. 209–219, 2020. doi: 10.1080/19393555.2020.1741742.

[35] C. Zhou, J. Huang, F. Yang, and Y. Liu, “A hybrid fusion model of iris, palm vein and finger vein for multi-biometric recognition system,” *Multimedia Tools and Applications*, vol. 79, no. 39–40. pp. 29021–29042, 2020. doi: 10.1007/s11042-020-08914-6.

[36] M. S. Wajid, S. G. Kumar, N. Baishwar, A. Singh, and P. Verma, “Palm and Fingerprint Based Multimodal Biometric Technique.pdf.” 2020.

[37] A. K. Yadav, “Deep Learning Approach for Multimodal Biometric Recognition System Based on Fusion of Iris, Fingerprint and Hand Written Signature Traits.Pdf.” 2021.

[38] C. Kamlaskar and and A. Abhyankar, “Iris-Fingerprint multimodal biometric system based on optimal feature level fusion model.pdf.” AIMS Electronics and Electrical Engineering, 5(4): 229–250., 2021.

[39] T. Kumar, S. Bhushan, and S. Jangra, “An Improved Biometric Fusion System of Fingerprint and Face using Whale Optimization .Pdf.” 2021.

[40] T. Vijayakumar, “Synthesis of Palm Print in Feature Fusion Techniques for Multimodal Biometric Recognition System Online Signature,” *J. Innov. Image Process.*, vol. 3, no. 2, pp. 131–143, 2021, doi: 10.36548/jiip.2021.2.005.

[41] B. Arjun and H. N. Prakash, “Multimodal Biometric Recognition System Using Face and Finger Vein Biometric Traits with Feature and Decision Level Fusion Techniques.pdf.” 2021.

[42] Channegowda a. b. and H. N. Prakash, “Multimodal biometrics of fingerprint and signature recognition using multi-level feature fusion and deep learnin... Indonesian.pdf.” 2021.

[43] P. P. Sarangi, D. R. Nayak, M. Panda, and B. Majhi, “A feature-level fusion based improved multimodal biometric recognition system using ear and profile face,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 4. pp. 1867–1898, 2021. doi: 10.1007/s12652-021-02952-0.

[44] H. Purohit and P. K. Ajmera, “Optimal feature level fusion for secured human authentication in multimodal biometric system,” *Machine Vision and Applications*, vol. 32, no. 1. 2021. doi: 10.1007/s00138-020-01146-6.

[45] G. Jaswal and R. C. Poonia, “Selection of optimized features for fusion of palm print and finger knuckle-based person authentication,” *Expert Systems*, vol. 38, no. 1. 2021. doi: 10.1111/exsy.12523.

[46] S. Tharewal *et al.*, “Score-Level Fusion of 3D Face and 3D Ear for Multimodal Biometric

Human Recognition Sumegh.pdf.” 2022.

[47] B. O. Mohammed, H. D. Majeed, S. Z. M. Hashim, and M. S. Al-Ani, “New Feature-level Algorithm for a Face-fingerprint Integral Multi- biometrics Identification System.pdf.” 2022.

[48] A. A. Joseph *et al*., “Person Verification Based on Multimodal Biometric Recognition Annie.pdf.” 2022.

[49] & S. Banati, U., Prakash, V., Verma, R., *Soft Biometrics and Deep Learning: Detecting Facial Soft Biometrics Features Using Ocular and Forehead Region for Masked Face Images*. 2022.

مسح على نهج الاندماج متعدد القياسات الحيوية

الخلاصة: *الهدف من هذه الورقة هو توزيع البحوث التي تم إجراؤها في مجال الاندماج البيومتري للمصادقة. تبدأ الدراسة بمناقشة الاختناقات المختلفة التي قد تواجهها أنظمة القياسات الحيوية أحادية النمط ، مع التركيز على ندرة المعلومات ، والاختلافات داخل الطبقة ، والعالمية ، والمقبولية. ركز المجتمع العلمي على دمج سمات القياسات الحيوية المتعددة كوسيلة للتغلب على هذه القيود. يقلل هذا المزيج من عيوب استخدام طريقة قياس حيوية واحدة مع زيادة فرصة وجود نظام مصادقة أكثر أمانًا في نفس الوقت. من حيث المنهجية المستخدمة والطرائق وقواعد البيانات المستخدمة والنتائج من حيث التعرف على الدقة ونسبة كفاءة الطاقة ، تناقش الورقة عددًا من الأوراق البحثية الحديثة. نوع الاندماج هو موضوع هذه المقالة لأنه يبدو أنه التصنيف الأكثر روعة الذي سيهتم به القادمون الجدد أو القراء. هذا التصنيف مهم لأنه يؤثر بشكل مباشر على الدقة التي يتم تحقيقها. الاندماج على مستوى النتيجة والمستوى المميز هو الأسلوب الأكثر عمومية ، ويمكن استنتاجه من الدراسة الشاملة المقدمة في هذا العمل. ومع ذلك ، يجب أن تقع الدرجات الخاصة بطريقتين أو أكثر في نفس النطاق حتى تكون ناجحة. خلاف ذلك ، قد تؤدي عدم الدقة الناتجة عن تطبيع الدرجات في النهاية إلى فقدان المعلومات وضعف الدقة. من ناحية أخرى ، يتم إعاقة اندماج مستوى الميزة بسبب الطبيعة غير المرتبطة للميزات وزيادة الأبعاد .ومع ذلك ، لا يمكن اعتبار الاندماج على مستوى المستشعر بمثابة استراتيجية اندماج مقبولة عالميًا لأنه غالبًا ما يكون من الصعب للغاية دمج الطرائق ذات الصلة على مستوى المستشعر. أخيرًا وليس آخرًا ، الاندماج على مستوى القرار - الذي يتم تنفيذه بعد الوصول إلى القرار من قبل المصنفين المختلفين - حساس جدًا لدقة كل مصنف ، مما قد يؤدي إلى اختيارات متحيزة أو غير دقيقة. بالإضافة إلى ذلك ، يمكن استنتاج أن غالبية محاولات الأدب تركز على دمج الطرائق التي ينتجها نفس الجزء أو المنطقة من الجسم. على سبيل المثال ، كانت هناك محاولات مختلفة لدمج قدرات هندسة اليد ، وبصمات الأصابع ، وبصمة الإصبع ، وبصمة اليد ، وراحة النخيل. على غرار هذا ، هناك الكثير من الاهتمام بدمج المقاييس من صور القزحية والوجه ومحيط العين والعين. ومع ذلك ، إذا تم الجمع بين طرائق من موقعين جسديين منفصلين ، فقد يتم تحقيق تأثيرات مثيرة للاهتمام من الأهمية بمكان تحليل هذه الاكتشافات والتطورات للأبحاث المستقبلية نظرًا للتقدم المتزايد في الذكاء الاصطناعي في العديد من مجالات الحياة. كان مطلوبًا مراجعة الدراسات المنشورة مؤخرًا في هذا المجال لأن الاندماج الحيوي باستخدام تقنيات التعلم العميق هو أحد مجالات الدراسة التي كانت نشطة في السنوات العشر الماضية .*