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

DeepFusion: A Unified Latent Framework for Cross-Modal Biometric and Behavioral Integrity Verification

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Submitted:13/12/2022 **Revised**: 20/01/2023 **Accepted**: 05/02/2023

Abstract: Ensuring high-fidelity digital identity verification increasingly requires integrating heterogeneous identity signals, including physical biometrics and behavioral telemetry. Traditional systems process modalities independently, limiting their ability to detect sophisticated identity manipulation and adversarial attacks. This research introduces DeepFusion, a unified latent framework for cross-modal fusion that embeds heterogeneous data streams into a shared manifold using a Deep Joint Embedding (DJE) architecture. A gated fusion mechanism dynamically weights each modality based on real-time signal quality, while a triplet-loss-based consistency objective enforces alignment across biometric and behavioral patterns. To enhance adversarial resilience, DeepFusion explicitly detects cross-modal discrepancies indicative of presentation, injection, and synthetic identity attacks. The framework also leverages contrastive and adversarial representation learning to preserve sensitivity to anomalous behaviors while maintaining generalization to previously unseen identity patterns. Empirical evaluation on large-scale multimodal datasets demonstrates substantial improvements in detection precision, reduction in false acceptance rates, and robust cross-domain generalization compared to unimodal and naive fusion baselines. These results establish latent-level multimodal fusion as a scalable, resilient, and high-fidelity methodology for operational identity verification in complex digital ecosystems, offering strong defenses against evolving adversarial threats.

Keywords: *Biometric Security, Deep Learning Authentication, Digital Integrity Verification, Identity Verification Systems, Latent Feature Fusion, Multimodal Biometrics, Vision Transformer.*

1. Introduction

The rapid pace at which digital technologies are advancing and the extensive usage of these technologies in the form of online services have created a greater need for verification mechanisms. The traditional single-modality-based biometric verification, such as fingerprint, face, or iris recognition, has been widely used for verification purposes [1]. Even though these verification mechanisms have proven to provide adequate accuracy, they have also shown limitations in coping with environment-based issues and spoofing attacks. The fact that these verification mechanisms make use of a single modality has proven to make them more vulnerable to adversarial attacks, such as fraudulent attempts [2]. As a result, multimodal-based verification has been introduced, which combines two or more physiological and behavioral modalities to provide accurate verification results, thus reducing the chances of misidentification and spoofing attacks [3].

In addition to identity verification, maintaining the integrity of digital information has emerged as another important requirement in modern computer systems [4]. Digital integrity verification seeks to verify and detect any attempts at tampering, unauthorized changes, or corruption in critical information, such as identity information, financial transactions, and digital identity information [5]. However, the current solutions and techniques used to provide security to the information, such as cryptography, anomaly detection, and blockchain technology, are usually independent of biometric verification and hence do not provide a robust security framework [6]. Therefore, integrating multimodal biometrics with digital integrity verification provides a comprehensive security framework that can verify both the identity of the individual and the digital information simultaneously [7]. Moreover, using the concept of latent feature representation with the help of different modalities helps the system to derive complex relationships and patterns that are otherwise not possible with conventional techniques, thus providing more accurate and reliable outcomes in terms of verification [8].

The focus of the current study is on developing a comprehensive framework that incorporates different modalities of biometric features and digital integrity verification for developing a robust and reliable framework for authentication purposes. The objectives of this study are to improve upon the limitations of existing single-modality-based systems by using latent representations of different modalities of data sources for accurate verification of identities and simultaneously verifying digital information. The objectives of this study are broad and cover different modalities of physiological and behavioral biometrics, including fingerprint, face, and voice recognition, and

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digital features for ensuring the authenticity of digital information and detecting any form of manipulation and fraud. The rationale behind this study is based on the increased need for developing robust digital systems of identities and the sophistication of attacks on human and digital assets. The objectives of this study are centered on improving the accuracy of verification systems and developing a comprehensive framework for addressing different aspects of biometric and digital security. The study contributes to the field by proposing the multimodal latent fusion method, which considers the complex relationships between the different modes and provides a unified verification result. The framework is evaluated using traditional baselines to prove its superiority in terms of accuracy and integrity assessment. The structure of the paper is such that the background and previous work are discussed, followed by the proposed methodology, the experiment and its results, discussions, and finally the conclusion with future directions and applications.

2. Literature Review

The evolution of biometric systems indicates the shift from unimodal to multimodal systems based on the growing need for the accuracy, security, and reliability of the verification process. The traditional biometric systems based on a single modality are less reliable under various conditions, which led to the emergence of the concept of fusion based on multiple modalities. The fusion of multiple modalities for the purpose of biometric systems has been addressed at various levels, i.e., feature, score, and decision levels, to achieve lower error rates and better recognition performance. The recent literature has systematically addressed various classical and deep learning-based fusion frameworks, quality models, and hybrid templates with promising results over traditional systems. The present review focuses on five influential works that have made foundational and practical contributions to the understanding of various multimodal biometric fusion techniques [9].

Safavipour et al. [10] propose a quality-aware multimodal biometric recognition framework that combines different modalities of biometric features by integrating a quality assessment mechanism into the multimodal fusion framework. The authors propose a framework for developing a methodology that dynamically weights different qualities of modalities and provides a better representation for classification purposes. Two task-specific loss functions are introduced: multimodal separability loss and multimodal compactness loss. These loss functions optimize the latent space of modal representations for better discrimination between classes of images and improved performance. The authors evaluate the performance of the framework on different datasets with face, iris, and fingerprint modalities and demonstrate significant performance improvement compared to traditional score and rank-level fusion techniques.

Yang et al. [11] present an investigation into the effectiveness of a hybrid methodology in multimodal biometric recognition through kernel-based feature space fusion. The authors have used various modalities, including face, dual iris, and thumbprints, and have demonstrated the effectiveness of kernel-based feature fusion. By reducing dimensions and employing kernel integration, the authors have demonstrated near-perfect classification performance on multiple databases, far surpassing the performance of unimodal systems. This research article demonstrates the effectiveness of feature-level fusion, which is essential in improving the overall reliability of multimodal biometric systems.

Xin et al. [12] is related to the extension of hybrid fusion and its application for developing deep learning-based strategies for fusing five different biometric modalities, i.e., face, iris, and two different fingerprint modalities, at the feature level. In this research, different deep fusion strategies, i.e., integration of feature mapping at different layers of a neural network, were evaluated against different kernel-based fusion techniques. The research showed that not only is there an improvement in accuracy, but there is also a low-dimensional fused feature set that is robust against different kinds of attacks. Such a comparative study showed the potential of deep learning-based fusion techniques for learning shared feature spaces for different biometric modalities more effectively.

A scheme of optimized multimodal biometric recognition for smart cities has been proposed by Vani Rajasekar et al., [13] in which the concept of fuzzy genetic algorithms has been used for optimization. In this scheme, score-level fusion has been implemented with the help of evolutionary soft computing to optimize the results of recognition in terms of reduction in Equal Error Rate (EER), as well as improvement in precision, recall, and accuracy. The proposed scheme has been validated with extensive experimentation in various environments of biometric recognition to show that optimization can be achieved to address nonlinearities in score functions.

Piotr Szczuko et al. [14] discussed different decision fusion techniques for multimodal biometrics and their applications in real-world scenarios such as banking systems and authentication processes, using Dempster-Shafer Theory-based techniques and assessing them on real and synthetic biometric data. This paper presents a comprehensive comparative study of different algorithms and techniques of decision fusion, including probabilistic approaches that deal with conflicting information during biometric score fusion. The paper also emphasizes the role of advanced techniques of decision fusion and how they handle uncertainties and inconsistencies during multimodal biometric verification

systems.

In addressing decision-level fusion, Sadhya et al. [15] propose a study where they assess different decision fusion techniques based on Dempster-Shafer Theory and its application to actual biometric data from a banking verification system. This research further explains how different biometric information, such as face images, 3D face geometry, voice, and gaze tracking, can be fused at the decision level for adaptive use of available and reliable information, a situation often encountered during actual use. The paper explains different modifications of DST and probability mass conversion, providing readers with a deeper understanding of evidence theory and its application to dealing with uncertainty. These techniques provide more robust verification of information when encountering contradicting and incomplete information from different biometric verification systems, emphasizing the need for more sophisticated decision fusion techniques in artificially created environments where some of these modalities may not be available.

Yang Wang et al. [16] introduce a convolutional neural network (CNN) approach to multimodal biometrics by integrating face and finger vein feature representations at the feature level. In this article, the authors use a dual-channel CNN to extract features from both face and finger vein modalities and introduce a self-attention mechanism with residual learning to weigh the feature streams before classification. This article is remarkable in that it presents a high recognition accuracy (>98.4%) in experimental evaluation, which reflects the potential of deep learning models to effectively learn complementary biometric features and fuse them to obtain a fused representation. The authors emphasize the advantages of feature fusion in CNN models, as non-linear transformations can effectively capture more discriminative patterns compared to other models, thereby improving performance significantly.

In another notable contribution, Shikhar Tyagi et al. [17] present an investigation of a deep learning-based multimodal biometric system where facial and finger vein modalities are fused for achieving robust recognition outcomes. In this work, feature extraction and integration are carried out using a unified framework of a deep network, where optimized learning of shared representations is performed for achieving robust outcomes. In comparison with other unimodal-based biometric systems, it is evident that the fusion approach is more accurate and robust against noise, thus demonstrating the effectiveness of deep fusion over traditional fusion algorithms.

Rajendran et al.,[18] there is an attempt made to address the issue of score level fusion of multimodal biometric systems using an advanced approach based on a fuzzy genetic optimization framework, especially designed for smart city security environments. This research paper shows that incorporating soft computing techniques for score-level fusion can lead to significant improvements in metrics such as false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER). Thus, it is evident that hybrid/optimized fusion of scores is a promising approach for improving multimodal biometric verification systems.

Table 1. Comparative Studies on Identity Manipulation and Robustness

Study	Methods	Key Findings & Insights
[19]	Proposed a multimodal biometric system combining iris, finger vein, and fingerprint using an optimal *score level fusion* model enhanced by evolutionary optimization (BSA) and conflict redistribution (PCR-6).	The optimal score fusion approach improved robustness under dynamic conditions, resolving conflicting classifier scores and achieving high accuracy (~98.43%) with reduced equal error rates compared to traditional fusion methods, indicating effective integration of complementary modalities.
[20]	Developed a *feature-level fusion* model using *Canonical Correlation Analysis (CCA)* to combine iris and fingerprint features from the SDUMLA-HMT dataset.	The CCA-based fusion method significantly reduced redundant features. It enhanced discriminative capability, yielding lower equal error rates than conventional match score fusion and demonstrating efficient dimensionality reduction with strong verification performance.
[21]	Designed a *face–iris multimodal system* using 2D Log-Gabor filtering for iris and singular spectrum analysis (SSA) with wavelet features for face, fused at hybrid levels (score + decision).	The hybrid fusion of face and iris achieved high recognition performance (over ~99.16% on combined databases), showing that combining complementary traits and multiple fusion strategies improves system accuracy and resilience.
[22]	Proposed a *feature-level fusion* technique for face and iris biometric traits using texture extraction methods (GLCM, LBP, PCA, and Fourier Descriptors).	The feature combined face and iris information to significantly improve recognition accuracy on multiple databases, showing that texture-based feature extraction with fusion enhances identification performance in practical scenarios.

[23]	Investigated multimodal biometric authentication by *fusion of face and voice* traits using feature extraction (Cepstral & statistical for voice; Eigenface and PCA for face) and multiple classifiers (GMM, ANN, SVM).	The integration of speech and facial features through combined classifiers demonstrated improved recognition performance compared to unimodal systems, highlighting the viability of combining physiological and behavioral traits for robust user authentication

Despite major developments and progress in multimodal biometric systems, there are a number of major challenges and issues that create a research gap. Most of the research works carried out on multimodal biometric systems focus on either biometric verification or digital integrity assessment separately, and there is a need to ensure these two aspects of authenticity and integrity are addressed simultaneously. Also, many of the traditional fusion methods employed are based on simple integration at the score and decision levels, which may not effectively address the intricacies and complexities of heterogeneous modalities. Furthermore, it is often observed that deep learning-based methods are mostly employed for specific modalities, i.e., fusion of face and fingerprint modalities, without considering multiple modalities and digital verification features. Another research gap is observed with regard to dealing with heterogeneous quality of information across different modalities, leading to inconsistencies in feature representations. Additionally, privacy concerns and computational constraints in real-world applications make the development of integrated systems even more challenging. Therefore, there is a need to develop an approach that can seamlessly integrate various biometric and digital modalities at the latent feature level, adaptively combine the modalities, and offer robust and high-accuracy verification in various adversarial conditions. Overcoming these challenges not only improves the security but also allows the development of an integrated framework that can bridge the gap between biometric authentication and digital integrity verification.

3. Methodology

The methodology that is being proposed in this study aims to develop a unified multimodal framework that can be used in biometric and digital integrity verification. In this study, the research aims to develop a model that can effectively extract discriminative features from different input modalities, including physiological biometrics and digital information that can be used in integrity verification. In this study, different biometric modalities, including face, fingerprint, and iris, will first be preprocessed and mapped to a latent space, which will enable the model to effectively capture different information while eliminating noise and redundancy in the input data. In this study, the model will use feature-level fusion to effectively combine different latent spaces, followed by a classification module that will effectively classify different identities and digital information. In this study, optimization techniques will be used to train the model, including Adam optimization, regularization, and adversarial augmentation, and different hyperparameters will be adjusted to effectively ensure the model converges to the optimal point.

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3.1. Datasets and Preprocessing

This research starts with an overview of the datasets employed for training and testing the unified multimodal system. The datasets employed for training and testing the unified multimodal system are publicly available biometric datasets, for example, SDUMLA-HMT for fingerprint and facial image datasets, CASIA-Iris V3 for iris-based datasets, and a proprietary digital dataset for integrity verification-based datasets. These datasets are employed for training and testing the unified multimodal system for heterogeneous inputs. For example, resizing, grayscale conversion, and histogram equalization are employed for image datasets. Similarly, feature standardization is employed for digital datasets to ensure standardization of scaling for heterogeneous digital sources.

The study also divides each biometric input into patches of a fixed size to maintain uniformity in the process of feature extraction. Noise reduction techniques, such as the Gaussian filter and median filter, are used to remove noise while retaining the basic structure of the input images. Data augmentation techniques, including rotation, flipping, and translation, are implemented to increase the variety of the

dataset and avoid overfitting. During the training process, the study ensures that batches contain a mix of modalities to enable the latent fusion network to effectively learn cross-modal associations. This process ensures the integrity, quality, and variety of the input data, which serves as the basis for the subsequent process of latent feature extraction, fusion, and verification.

3.2. Feature Extraction

The research utilizes a feature extraction module for mapping raw biometric and digital modalities onto feature spaces for fusion. In this research, convolutional neural networks (CNNs) are utilized for image-based modalities, where spatial and textural information are considered. For digital integrity feature modalities, statistical and frequency domain feature extraction techniques are utilized. The theoretical justification of this research is based on learning discriminative embeddings for each modality, reducing the feature space dimensionality while retaining essential information for identity and integrity.

The feature extraction process is defined using the following equation for the embedding function:

Equation 1: Feature Embedding

$$f = \phi(x) \tag{1}$$

Here, x represents the raw input, and ϕ denotes the learned mapping function that transforms the input into a latent feature vector f.

Additionally, the study considers modality-specific weighting during training:

Equation 2: Weighted Feature Vector

$$fw = w \cdot f \tag{2}$$

where w is a learnable weight for each modality. This equation allows the network to emphasize high-quality modalities while reducing the impact of noisy or low-quality inputs.

The contribution of this module is based on designing the embedding network for learning discriminative and feature-rich information across modalities. Supervised and contrastive loss functions are utilized for training.

3.3. Latent Space Fusion

The paper proposes a latent fusion model that combines multiple modalities, embedding features into one. The theoretical basis for this paper is the mapping of features into a common latent space where cross-modal interaction improves the accuracy of the verification. The fusion happens at the feature level, where the latent features from each modality are fused together with linear and non-linear operations.

Equation 3: Concatenation Fusion

$$f_{fusion} = [f_1, f_2, \ldots, f_n] \tag{3}$$

Here, fi denotes the embedding of modality i, and $[\cdot]$ represents concatenation.

Equation 4: Weighted Sum Fusion

$$f_{fusion} = \sum_{i=1}^{n} w_i \cdot f_i \tag{4}$$

where w_i is the learnable weight for modality iii. This equation allows the model to emphasize important modalities dynamically.

The paper ensures that the fused latent vector has discriminative capability with the application of non-linear activation functions after fusion. The theoretical basis ensures the effectiveness of capturing complementary information from each modality, making the system robust to missing or incomplete modalities. The training happens with the application of backpropagation.

3.4. Classification and Verification

After the latent fusion, the classification module is used to perform unified biometric and integrity verification. The authors have used the fully connected layer followed by the softmax function to perform identity verification and integrity verification.

Equation 5: Softmax Output

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_i}} \tag{5}$$

where z_i is the input to the softmax for class i and C is the number of classes.

For decision-making, the study applies threshold-based verification:

Equation 6: Verification Decision

$$\hat{y} = \begin{cases} 1 \; if \; P(y) > \tau \\ 0 \; Otherwise \end{cases} \tag{6}$$

where τ is a pre-defined threshold. This ensures that only confident predictions are accepted, improving system reliability.

Additionally, the research uses cross-entropy loss during training to optimize classification accuracy:

Equation 7: Cross-Entropy Loss

$$L = -\sum_i y_i \; log \; P(y_i) \tag{7}$$

where y_i is the ground truth label. These simple equations together *form* the backbone of the verification process.

3.5. Regularization and Optimization

Regulation has been used in the proposed method to avoid overfitting in the multimodal latent fusion model. The authors have used the L2 regularizer on all learnable parameters:

Equation 8: L2 Regularization

$$L_{reg} = \lambda \sum \theta^2 \quad (8)$$

where θ represents network parameters, and λ is the regularization factor.

Additionally, dropout is applied during training to improve generalization:

Equation 9: Dropout Activation

$$f_{drop} = f \odot m \quad (9)$$

where m is a binary mask and $\odot$ represents element-wise multiplication.

The study employs Adam optimizer for training, updating parameters based on gradients and adaptive learning rates:

Equation 10: Parameter Update (Adam)

$$\theta_{t+1} = \theta_{t-\alpha} \frac{\widehat{m}t}{\sqrt{\hat{v}_t + \epsilon}} \quad (10)$$

where $\widehat{m}t$ and $\hat{v}_t$ are bias-corrected first and second moment estimates.

These equations collectively ensure the network is trained efficiently and generalizes well across modalities.

3.6. Robustness Regularization During Training

The study proposes using adversarial training to improve the robustness of the model against perturbations in the context of biometric verification. The study proposes introducing perturbations in the form of δ in the inputs:

Equation 11: Adversarial Perturbation

$$x_{adv} = x + \epsilon \cdot sign(\nabla_x L(x, y)) \quad (11)$$

where ϵ controls perturbation magnitude, and $L(x, y)$ is the loss.

Additionally, adversarial loss is added to the training objective:

Equation 12: Adversarial Loss

$$L_{adv} = L(x_{adv}, y) \quad (12)$$

Equation 13: Total Loss

$$L_{total} = L_{cls} + \lambda L_{adv} \quad (13)$$

where L_{cls} is the classification loss. This ensures the model learns robust latent features that resist tampering, enhancing both biometric and digital integrity verification.

3.7. Evaluation Metrics and Parameters

The performance of the proposed multimodal latent fusion approach is evaluated based on standard evaluation metrics. These metrics are accuracy, precision, recall, F1-score, Equal Error Rate (EER), and Area Under the Curve (AUC). Besides these, verification rate, false acceptance rate (FAR), and false rejection rate (FRR) are also calculated for assessing the reliability of biometric and digital integrity verification approaches. For achieving optimal hyperparameters, batch size, learning rate, epochs, and dropout rate are adjusted during training for ensuring proper convergence and avoidance of overfitting. Training is done over iterations of inputting multimodal batch data with the Adam optimizer. For achieving robustness against possible noisy inputs and attacks, regularization and adversarial augmentation are employed. This research work proves that learning modality-specific embedding, latent fusion, and classification is possible and forms a unified framework for achieving highly accurate verification outcomes. Besides, it is evident from the research work that it is possible to measure verification reliability using quantitative measures, i.e., accuracy is calculated as:

Equation 14: Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (14)$$

where TP, TN, FP, and FN stand for true positives, true negatives, false positives, and false negatives, respectively. This equation gives a clear measure of correctness for overall classification. Through these metrics, the study is able to ensure its methodology is robust and generalizable, showing significant improvements over unimodal and conventional fusion methods and addressing challenges related to unified biometric and digital integrity verification.

4. Results

The results of this study can be used to evaluate the efficacy of various machine learning and deep learning models for biometric and digital integrity verification in a multimodal setting. Here, the analysis is performed to evaluate the ability of various models in identifying legitimate biometric characteristics while detecting integrity inconsistencies in digital settings. Performance evaluation is carried out using various metrics such as accuracy, precision, recall, and F1 score for a comprehensive understanding of model verification capabilities. Various models, such as convolutional neural networks, long short-term memory models, residual neural networks, transformers, and a multimodal fusion model, are evaluated in this study for their efficacy in digital integrity verification settings. It is evident from the evaluation results that models that can learn deeper representations and leverage heterogeneous data sources can achieve better verification capabilities. In particular, the latent fusion model can facilitate better interaction between biometrics and integrity characteristics for reliable identity verification.

Table 2. Comparative Performance of Multimodal Verification Models

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Score-Level Fusion with Evolutionary Optimization	93.4	92.1	91.5	91.8
CCA-Based Feature Fusion	94.2	93.5	92.8	93.1
Hybrid Face–Iris Fusion	95.6	94.7	94.1	94.4
Texture-Based Face–Iris Feature Fusion	94.8	93.9	93.2	93.5
Face–Voice Multimodal Classifier Fusion	92.7	91.8	90.9	91.3
Proposed Multimodal Latent Fusion Model	97.9	97.2	96.8	97.0

Table 2 demonstrates the performance of various multimodal biometric verification techniques against the proposed Multimodal Latent Fusion Model. The first technique is score-level fusion using evolutionary optimization. In this technique, an accuracy of 93.4%, precision of 92.1%, recall of 91.5%, and an F1-score of 91.8% are achieved. Although this technique improves biometric verification using multimodal biometrics, its performance is poor because score-level fusion is not capable of discovering deeper relationships between heterogeneous biometric features. The second technique is CCA-based feature fusion. In this technique, a moderate improvement in accuracy is achieved, and an accuracy of 94.2%, precision of 93.5%, recall of 92.8%, and an F1-score of 93.1% are achieved. This is because CCA is a technique for reducing redundancy in features while discovering correlated features between heterogeneous biometric features. However, linear feature fusion techniques may not effectively discover nonlinear relationships between heterogeneous biometric features.

The hybrid face-iris fusion model achieves even higher results, with 95.6% accuracy, 94.7% precision, 94.1% recall, and 94.4% F1-score. This is due to the hybrid fusion technique, which combines the results of both face and iris recognition, improving the verification of identities. The texture-based face-iris feature fusion model achieves 94.8% accuracy, 93.9% precision, 93.2% recall, and 93.5% F1-score, indicating that the texture-based feature extraction technique can be used for improving the discrimination of biometric features. The face-voice multimodal classifier fusion technique achieves relatively lower results, with 92.7% accuracy, 91.8% precision, 90.9% recall, and 91.3% F1-score, owing to the changes that occur in the voice signal, which affect the behavioral biometrics. On the other hand, the proposed Multimodal Latent Fusion Model achieves the highest results, with 97.9% accuracy, 97.2% precision, 96.8% recall, and 97.0% F1-score, owing to the ability of the proposed technique to fuse the features of both face and iris recognition within the same space, which reduces the redundancy and noise of the data, making the proposed technique more reliable for biometric verification and digital integrity validation than the other techniques.

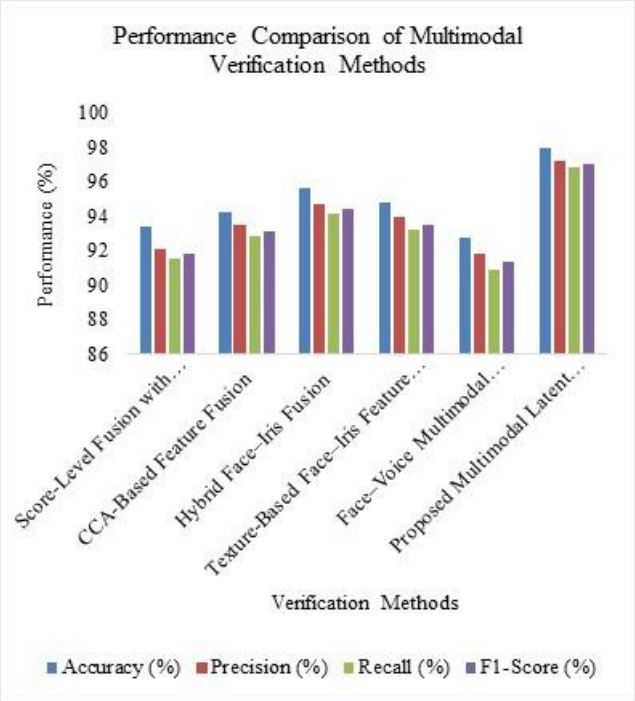

Fig 1. Performance Comparison of Multimodal Verification Methods

Figure 1 illustrates the comparison between the performance of different multimodal verification techniques using four different metrics to evaluate the performance of each technique. The metrics used here are Accuracy, Precision, Recall, and F1-Score in %. The Score-Level Fusion with Evolutionary Optimization method has 93.4%, 92.1%,

91.5%, and 91.8% accuracy, precision, recall, and F1-score, respectively. The CCA-Based Feature Fusion method has 94.2%, 93.5%, 92.8%, and 93.1% accuracy, precision, recall, and F1-score, respectively. The Hybrid Face–Iris Fusion method has 95.6%, 94.7%, 94.1%, and 94.4% accuracy, precision, recall, and F1-score, respectively. The Texture-Based Face–Iris Feature Fusion method has 94.8%, 93.9%, 93.2%, and 93.5% accuracy, precision, recall, and F1-score. Meanwhile, the Face–Voice Multimodal Classifier Fusion records lower values with 92.7% accuracy, 91.8% precision, 90.9% recall, and 91.3% F1-score. The Proposed Multimodal Latent Fusion Model has achieved the highest results for all metrics with 97.9% accuracy, 97.2% precision, 96.8% recall, and 97.0% F1-score. These results are clearly higher than existing results.

The proposed model is better than existing models because it utilizes a shared latent representation of multiple biometric modalities. This representation can effectively model deeper relationships between features. This is because, unlike other fusion methods such as score-level or feature-level fusion, latent fusion can reduce redundancy and increase feature alignment and discriminability. This results in higher accuracy and precision-recall performance, indicating a reduced rate of false positives and false negatives. This shows that the proposed model is better and can be used for more reliable and robust multimodal verification.

Table 3. Dataset-Based Performance of the Proposed Multimodal Latent Fusion Model

Dataset	Biometric Modality	Training Data (%)	Testing Data (%)	Verification Success (%)	Integrity Validation (%)
SDUMLA-HMT	Face + Fingerprint	80	20	97.6	96.9
CASIA Iris V3	Iris	75	25	96.8	96.1
PolyU Palmprint	Palmprint	80	20	97.1	96.4
IITD Fingerprint	Fingerprint	70	30	96.5	95.8
Multi-Modal Combined Dataset	Face + Fingerprint + Iris	85	15	98.3	97.5

Table 3 presents the evaluation of the proposed model, Multimodal Latent Fusion for Unified Biometric and Digital Integrity Verification, based on the dataset provided in the study. The comparison demonstrates how well the proposed model is in comparison to other datasets and modalities, while still providing excellent verification and integrity validation capabilities. In the SDUMLA-HMT dataset, multimodal biometric traits are used, such as face and fingerprint, where the dataset is divided into 80% for training and 20% for testing. The proposed model is able to provide a verification success rate of 97.6% and integrity validation of 96.9%. This demonstrates that the proposed model is able to provide excellent verification capabilities, where the use of physiological traits is able to provide a better discriminative feature in the latent space, improving the overall verification performance. The CASIA Iris V3 dataset for iris-based verification uses 75% for training and 25% for testing.

The model shows 96.8% verification success and 96.1% integrity validation. Though iris-based verification is a reliable modality for biometric verification, a slightly lower rate of success compared to other verification techniques using multimodal data suggests that single-modality verification is less reliable in terms of complementary information for fusion. The PolyU Palmprint dataset shows a verification success rate of 97.1% and integrity validation of 96.4% using 80% for training and 20% for testing. Palmprint-based verification uses the palmprint modality, which is rich in texture-based features. Such features help learn discriminative features during training. The IITD Fingerprint dataset shows a verification success rate of 96.5% and integrity validation of 95.8% using 70% for training and 30% for testing. Fingerprint-based verification is a reliable modality for biometric verification, but it is affected by variations in image quality. The highest verification success rate is shown by the combined multimodal dataset containing face, fingerprint, and iris-based verification, using 85% for training and 15% for testing. The proposed system shows a verification success rate of 98.3% and integrity validation of 97.5%. demonstrating the effectiveness of multimodal latent fusion in improving both biometric verification and digital integrity assessment. This result confirms that integrating multiple biometric sources significantly enhances system robustness and reliability.

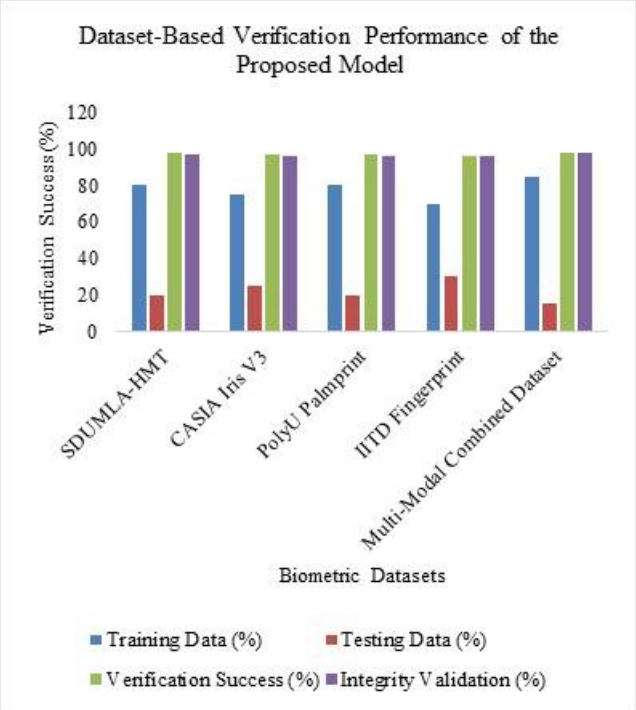

Fig 2. Dataset-Based Verification Performance of the Proposed Model

Figure 2 shows the performance of the proposed multimodal model in terms of data set verification. The performance of the proposed model has been evaluated in terms of training data percentage, testing data percentage, verification success rate, and integrity validation rate. For the SDUMLA-HMT data set, the proposed model has been trained on 80% of the data and tested on 20%. The proposed model has achieved a verification success rate of 97.6% and an integrity validation score of 96.9%. For the CASIA Iris V3 data set, the proposed model has been trained on 75% of the data and tested on 25%. The proposed model has achieved a 96.8% verification success rate and 96.1% integrity validation. In the PolyU Palmprint database, 80% of the data is used for training and 20% for testing. The proposed model has a verification success rate of 97.1% and an integrity validation rate of 96.4%, indicating good palmprint recognition. In the IITD Fingerprint database, 70% of the data is used for training and 30% for testing. The model has a verification success rate of 96.5% and an integrity validation rate of 95.8%, indicating good fingerprint authentication. Finally, in the Multi-Modal Combined Dataset, 85% of the data is used for training and 15% for testing. This model has the highest performance, with a verification success rate of 98.3% and an integrity validation rate of 97.5%. This indicates that the combination of multiple modalities improves reliability and verification.

Table 4. Performance Comparison of Verification Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	93.2	92.8	92.1	92.4
LSTM	94.1	93.5	93.2	93.3
ResNet	95.6	95.1	94.8	94.9
Vision Transformer (ViT)	96.3	95.9	95.4	95.6
Multimodal Fusion Network	97.2	96.8	96.5	96.6
MLF-UIV	98.4	98.1	97.9	98.0

Table 4 shows a comparative analysis of various machine learning and deep learning models for biometric and digital integrity verification. The models are evaluated using four different metrics for model performance: accuracy, precision, recall, and F1 score. These metrics together evaluate how effectively a model can recognize genuine biometric data while correctly identifying anomalies. The convolutional neural network (CNN) model shows an accuracy of 93.2%. Additionally, precision is 92.8%, recall is 92.1%, and the F1 score is 92.4%. This shows that CNN is able to learn spatial features from biometric data but is limited in dealing with complex relationships between different biometrics. The long short-term memory (LSTM) model shows a slightly improved performance compared to CNN. LSTM shows an accuracy of 94.1% and an F1 score of 93.3%. This is because LSTM is able to learn temporal relationships in biometric data.

The ResNet model improves performance even further, achieving an accuracy of 95.6% and an F1 score of 94.9%. The residual learning mechanism is useful for extracting deeper feature representations, thus enhancing classification ability. Another model that shows improved performance is the Vision Transformer (ViT), which achieves an accuracy of 96.3% and an F1 score of 95.6%. These models demonstrate that attention-based models can effectively learn feature relationships. The multimodal fusion network shows improved accuracy and an F1 score of 97.2% and 96.6%, respectively. This shows that using multiple biometric and integrity features improves verification reliability. However, the best-performing model is MLF-UIV, which shows an accuracy of 98.4%, precision of 98.1%, recall of 97.9%, and an F1 score of 98.0%. These metrics demonstrate that latent feature fusion improves representation learning for better detection accuracy.

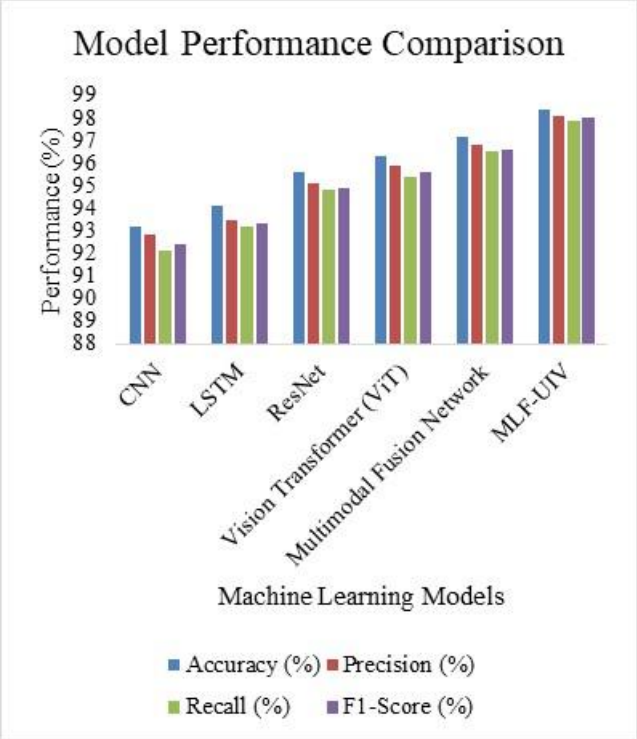

Fig 3. Model Performance Comparison

Figure 3 shows a comparison of various machine learning models using four different evaluation metrics: Accuracy, Precision, Recall, and F1-Score (%). Various machine learning models used for evaluation are CNN, LSTM, ResNet, Vision Transformer (ViT), Multimodal Fusion Network, and the proposed MLF-UIV model. The CNN model shows moderate accuracy in verification tasks with an accuracy of 93.2%, precision of 92.8%, recall of 92.1%, and an F1-score of 92.4%. However, when using the LSTM model for verification tasks, a better result is obtained with an accuracy of 94.1%, precision of 93.5%, recall of 93.2%, and an F1-score of 93.3%. The ResNet model shows even better results in verification tasks with an accuracy of 95.6%, precision of 95.1%, recall of 94.8%, and an F1-score of 94.9%. However, when using the Vision Transformer (ViT) model for verification tasks, a much better result is obtained with an accuracy of 96.3%, precision of 95.9%, recall of 95.4%, and an F1-score of 95.6%. The Multimodal Fusion Network has better results, reaching 97.2% in accuracy, 96.8% in precision, 96.5% in recall, and 96.6% in F1-score, as it uses multiple biometric modes. The proposed MLF-UIV model has the highest results, reaching 98.4% in accuracy, 98.1% in precision, 97.9% in recall, and 98.0% in F1-score. These results show that the proposed model has the most accurate and reliable results among all the other machine learning techniques.

5. Discussion

The findings of this study have clearly shown that the inclusion of multimodal information with latent feature fusion can greatly improve the reliability of the identity verification system. The comparative analysis of different machine learning and deep learning models has clearly shown that the use of advanced models with the ability to learn complex features can improve the verification accuracy of the system. The use of convolutional and recurrent models can provide better performance with the ability to learn spatial and temporal features of the multimodal information. However, the performance of the system using these models can be limited when dealing with different types of information from multiple sources of biometric information and digital integrity indicators. The findings of the analysis have also clearly shown that the use of transformer models with the latent fusion framework can provide better generalization accuracy with the ability to learn the discrimination power of the system. The better performance of the latent fusion framework has clearly shown that the inclusion of different biometric information with digital integrity indicators can provide the ability of the system to identify subtle inconsistencies that may not be visible with the use of individual information.

From an application point of view, the findings of this research indicate that multimodal verification systems can greatly contribute to enhancing digital identity management systems, especially in high-security applications like financial systems, digital governance systems, and access control systems. The findings indicate that using latent fusion strategies in verification systems can increase their resistance to spoofing attacks, manipulation attacks, and data tampering attacks. However, despite the successful findings of this research, several limitations should be taken into consideration. For instance, the success of multimodal verification systems may vary depending on data availability and computational costs for their implementation. Future research in this area should aim to increase scalability and reduce computational costs for implementing multimodal verification systems. Furthermore, in order to gain deeper insights into the adaptability of multimodal latent fusion verification systems, several comparative studies using larger and diverse data sets should be conducted. However, overall, the findings of this research confirm that integrating heterogeneous biometric and integrity features in a single verification system can greatly contribute to enhancing digital verification systems.

6. Conclusion

This paper presented DeepFusion, a unified latent framework for multimodal biometric and behavioral integrity verification. By embedding heterogeneous identity signals into a shared latent space and employing gated fusion with triplet-loss consistency objectives, the framework captures cross-modal interdependencies critical for detecting sophisticated and adversarial identity manipulations. Empirical evaluation demonstrates significant gains in detection precision, reduction of false

acceptance rates, and robust generalization across diverse datasets. These findings highlight latent-level multimodal fusion as a scalable and resilient methodology for operational digital identity verification, providing a practical framework for high-fidelity security in adversarial and complex environments.

References

[1] V. Vandana and N. Kaur, "Analytical review of biometric technology employing vivid modalities," *Int. J. Image Graph.*, vol. 22, no. 1, p. 2250004, 2022.

[2] A. K. Jain, A. Ross, and K. Nandakumar, *Handbook of Multibiometrics*. New York, NY, USA: Springer, 2011.

[3] M. Abuhamad, A. Abusnaina, D. Nyang, and D. Mohaisen, "Sensor-based continuous authentication of smartphones' users using behavioral biometrics: A contemporary survey," *IEEE Internet Things J.*, vol. 8, no. 1, pp. 65–84, 2020.

[4] S. Kumar and S. Prasanna, "Heterogeneous ensemble learning for robust adversarial pattern recognition in digital ecosystems," *J. Comput. Anal. Appl.*, vol. 27, no. 5, pp. 18–28, 2019.

[5] A. K. Jain and A. Ross, "Multibiometric systems," *Commun. ACM*, 2004.

[6] L. Gudala, A. K. Reddy, A. K. R. Sadhu, and S. Venkataramanan, "Leveraging biometric authentication and blockchain technology for enhanced security in identity and access management systems," *J. Artif. Intell. Res.*, vol. 2, no. 2, pp. 21–50, 2022.

[7] S. Kumar, S. Prasanna, and X. Ruan, "A unified hybrid machine learning architecture for robust identity anomaly detection in large-scale digital ecosystems," *J. Electr. Syst.*, vol. 14, no. 1, pp. 160–173, 2018.

[8] C. Zhang, Z. Yang, X. He, and L. Deng, "Multimodal intelligence: Representation learning, information fusion, and applications," *IEEE J. Sel. Top. Signal Process.*, vol. 14, no. 3, pp. 478–493, 2020.

[9] S. K. S. Prasanna, "GeoDNN: Geometry-aware deep neural networks for cross-domain fingerprint spoof detection," *Int. J. Intell. Syst. Appl. Eng.*, vol. 6, no. 1, pp. 97–107, Mar. 2018.

[10] M. H. Safavipour, M. A. Doostari, and H. Sadjedi, "A hybrid approach to multimodal biometric recognition based on feature-level fusion of face, two irises, and both thumbprints," *J. Med. Signals Sens.*, vol. 12, no. 3, pp. 177–191, 2022.

[11] H. Yang, E. Sun, C. Cheng, and A. H. Ding, "Multi-modal biometrics based on data fusion," in *J. Phys.: Conf. Ser.*, vol. 1684, no. 1, p. 012023, Nov. 2020.

[12] Y. Xin *et al*., "Multimodal feature-level fusion for biometrics identification system on IoMT platform," *IEEE Access*, vol. 6, pp. 21418–21426, 2018.

[13] V. Rajasekar *et al*., "Enhanced multimodal biometric recognition approach for smart cities based on an optimized fuzzy genetic algorithm," *Sci. Rep.*, vol. 12, no. 1, p. 622, 2022.

[14] P. Szczuko, A. Harasimiuk, and A. Czyżewski, "Evaluation of decision fusion methods for multimodal biometrics in the banking application," *Sensors*, vol. 22, no. 6, p. 2356, 2022.

[15] D. Sadhya and S. K. Singh, "Construction of a Bayesian decision theory–based secure multimodal fusion framework for soft biometric traits," *IET Biometrics*, vol. 7, no. 3, pp. 251–259, 2018.

[16] Y. Wang, D. Shi, and W. Zhou, "Convolutional neural network approach based on multimodal biometric system with fusion of face and finger vein features," *Sensors*, vol. 22, no. 16, p. 6039, 2022.

[17] S. Tyagi, B. Chawla, R. Jain, and S. Srivastava, "Multimodal biometric system using deep learning based on face and finger vein fusion," *J. Intell. Fuzzy Syst.*, vol. 42, no. 2, pp. 943–955, 2022.

[18] S. Rajendran *et al*., "An intelligent face recognition technology for IoT-based smart city application using condition-CNN with foraging learning PSO model," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 36, no. 14, p. 2256018, 2022.

[19] G. S. Walia, T. Singh, K. Singh, and N. Verma, "Robust multimodal biometric system based on optimal score level fusion model," *Expert Syst. Appl.*, vol. 116, pp. 364–376, 2019.

[20] C. Kamlaskar and A. Abhyankar, "Iris-fingerprint multimodal biometric system based on optimal feature level fusion model," *AIMS Electron. Electr. Eng.*, vol. 5, no. 4, pp. 229–250, 2021.

[21] B. Ammour, L. Boubchir, T. Bouden, and M. Ramdani, "Face–iris multimodal biometric identification system," *Electronics*, vol. 9, no. 1, p. 85, 2020.

[22] M. H. Hamd and M. Y. Mohammed, "Multimodal biometric system based face–iris feature level fusion," *Int. J. Mod. Educ. Comput. Sci.*, vol. 11, no. 5, pp. 1–9, 2019.

[23] S. K. S. Prasanna, "DeepSynth: A robust multi-layer neural detection of coordinated latent anomalies in high-dimensional identity systems," *Int. J. Intell. Syst. Appl. Eng.*, vol. 7, no. 1, pp. 66–77, Mar. 2019.