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OPTIMISED FINGERPRINT FEATURE REPRESENTATION FOR RELIABLE IDENTIFICATION

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ABSTRACT

The fingerprint recognition has become a widely used procedure of biometric authentication but its functionality is typically affected by noise, mis-alignment and partial impression of the fingerprint making the existing feature extraction and classification scheme ineffective. In an attempt to address these issues, the research shall recommend an adaptive model of fingerprint recognition that shall incorporate the application of enhanced feature extraction and effective classification methods. Specifically, it introduces the proposed algorithm Selective Spatio-Temporal Residual Feature Framework (STRFF-Net) of discriminative spatio-temporal features extraction and Temporal Residual Flow Recognition Network (TRFRN) of the accurate fingerprint identification. STRFF-Net uses the residual flow modeling and attention to highlight salient ridge and minutiae patterns and discard the irrelevant or noisy regions to provide enriched feature representation. TRFRN uses the stream of attention-based classification model to investigate the spatial and temporal changes patterns of the fingerprints that enables reliable recognition of the prints of fingers in the event of smudged and partial fingerprints. Comparison of the experimental results with publicly available fingerprint data shows that experimental analysis with reference to feature improvement, strength of the activation as well as accuracy of classification is highly improved when compared to existing and machine-based learning techniques. The robustness and precision of the suggested framework makes it a suitable instrument in the realistic application of biometric authentication, forensic identification or application in areas of serious security concern.

Keywords: *Attention Mechanism, Biometric Authentication, Fingerprint Recognition, Residual Flow, STRFF-Net, TRFRN.*

1. INTRODUCTION

The biometric authentication that is based on fingerprint identification has arrived, and it is one of the most deserving technologies of biometric identification because it is distinctive and dependable. It is a paradigm that is dependent on the capturing, processing, and analyzing of the properties of fingerprints to determine individuals with the correct mindset. The precision, strength, and practicality of the fingerprint matching systems have been argued over in the past few years with a myriad of techniques [1]. A case in point would be the application of the customary minutiae-based algorithms and the improved SIFT attributes as the high-visibility tool in the search for the accurate discriminatory fingerprint data [2].

It has also recently been developed into a partial fingerprint alignment scheme of joint identity verification, and it has a beneficial effect on the recognition in a hostile environment [3]. It was also synchronised with the capture of a fingerprint to a Siamese network affinity with adversarial learning, and other attributes of differences [4]. Furthermore, the biomedical images are visualised through deep learning structures as well as machine learning structures to improve the quality of diffraction of the print images with satisfactory results [5].

Models have been described based on fingerprints and applied to develop an indoor positioning system, and a research on forensics [6]. Fingerprints have been authenticated based on machine learning algorithms in the extraction of the minutiae coupled with the minutiae [7].

Fingerprint recognition systems. Fingerprint recognition systems have gone further to explore the systems, which are built on minutiae-based extraction and machine learning of the extracted minutiae [8]. Contactless recognition of the fingerprint is also implemented in order to promote its use and provision [9]. Multi-modal biometric systems are multi-modal; the dependent attributes enhance the capacity and the processes of the fingerprint recognition [10]. The researchs belonging to the literature review under analysis [11] concentrated on alternative ways of multimodal biometric recognition.

Other new surveys have also considered the emergent fingerprint recognition technology, deep learning structures [12], template protection structures [13], systematic structure [14], deep learning multimodal systems [15], and contactless spoofing detection with transfer learning structure [16]. The combination of the existing transforms and the deep learning network or model has been suggested to be used in some of the tasks, like the identification of the fingerprints of children [17]. Regressions and classifications have also been used to estimate the orientation by using these techniques to increase the accuracy of the fingerprint feature position [18]. The author have factored in the potential of the future of mass exploration of fingerprint collection intelligence in the area of indoor localisation and application of machine learning established recognition systems [19]. The concept of data enrichment and deep transfer learning has also been presented to augment the categorisation of patterns, reduce the degree of overfitting, and improve the ability of generalisation [20].

The research presents a new spatio-temporal residual flow and attention-based feature learning (STRFF-Net) approach to fingerprint recognition that is based on more than existing or incremental advancements. In contrast to the current approaches where mostly the use of the static spatial characteristics or the dataset-specific classifier is used, STRFF-Net is capable of processing incomplete, noisy, and shifted fingerprints and retains its computational performance. It combines both temporal dynamics and spatial attention to increase discriminative feature representation showing considerably higher recognition accuracy and robustness under a variety of real-world conditions. Therefore, the research offers innovative and significant knowledge as opposed to insignificant improvements, which is consistent with the best practices in fingerprint recognition research.

The fingerprint recognition methods that have been identified in the literature have toiled the current challenges that are linked with partial fingerprints, noisy inputs, poor quality inputs, environmental variability and differences between gadgets. The existing methods are for the most part based on fixed pools of fitting spatial features or computationally-intensive deep learners, which is a weakness to the resilience and practical use. In addition, there are no effective systems to capture temporal dependencies and selectively concentrate on discriminative features which reduces recognition accuracy in dynamic conditions. In a bid to address these gaps, the proposed research will set out to develop a spatio-temporal residual feature learning model with a stronger attention mechanism that is less prone to partial and noisy fingerprints, more discriminative across diverse environments and devices, and with a higher recognition accuracy and lesser computational power, as compared to the current fingerprint recognition models.

This research is organised as follows: in Section 1, to introduce fingerprint recognition, the significance of it in biometric authentication, and the challenge of achieving accurate feature extraction. In Section 2, to present the existing literature on fingerprint recognition, feature extraction approaches, multimodal biometrics, and indoor localisation. In Section 3, to present an overview of the proposed framework, including STRFF-Net for spatio-temporal residual feature selection and TRFRN for classification, as well as dataset preparation and preprocessing. Section 4 presents results of the experiments and a discussion of metrics for feature selection to classification performance and visualisations such as heatmaps for interpretation of the results. Finally, Section 5 concludes, summarises the contributions, provides evidence that it is effective and outlines future research.

2. BACKGROUND STUDY

Zhu et al. (2020) [21] examined the topic of indoor intelligent fingerprint-based localization, discussing the principles, methods, and challenges. The author presented survey and analysis techniques to make comparisons of existing techniques. The research gap that was defined was insufficient strength with dynamic indoor conditions and partial fingerprints. Findings indicated that existing accuracy is reduced in the presence of environmental variability.STRFF-Net is able to deal with dynamic and partial fingerprints and becomes more robust under different conditions in the indoor environment.

Chen et al. (2022) [22], The optimization of deep neural networks combined with multidetector to enhance the high-accuracy fingerprint positioning was the work, which was dedicated with Wi-Fi. The author used the signal processing DNN-based optimization. Weakness: no analysis in noisy realistic conditions. The results indicated that the positioning accuracy is improved in relation to the existing DNN models.STRFF-Net performs better in noisy real-world scenarios and uses spatio-temporal feature learning.

Yang et al. (2019) [23] offered a review of fingerprint-based biometrics security and accuracy, comparing existing and machine learning. The research gaps were incomplete partial fingerprint recognition and inter-sensor adaptation. The framework points out weaknesses of the conventional approaches to spoofing and partial fingerprint recognition.The framework enhances partial fingerprint recognition and cross-sensor adaptation.

Sonny and Kumar (2022) [24]. The Wi-Fi was confirmed on the basis of fingerprints and 3D localization of a building on CNN based multi-building indoor.CNN extraction of features was used as the spatial positioning. Reduce the huge scale computing complexity. Findings were a pointer to high levels of localization accuracy when compared to non- CNN models and furthermore, findings of STRFF-Net do not demand too much processing power and on the other hand, it possesses high levels of localization accuracy in large scale applications.

Kukreja et al. (2021) [25] recommended using deep learning to protect the template in order to improve privacy. The author used neural network encoded feature encoding and template protection. Restrictions: inability to flex cross sensors. The results depicted increased privacy and infringement reduction.The proposed system is cross-sensor adaptable and secure template of the fingerprints.

Mondal et al. (2025) [26] introduced a CNN -based, fake fingerprint identification system to secure human security. CNNs were used in the spoof detection. Limit: use of particular datasets, cross-device assessment is not involved. Findings indicated excellent detection and resistance to spoofed fingerprints.STRFF-Net can generalize across datasets and devices to partial and noisy fingerprints.

Shaheed et al. (2021) [27] performed a systematic review of the physiology-based biometrics recognition systems such as the fingerprint modalities. The author compared deep learning and conventional methods. scanty real-life cross-modality consolidations and validations. Findings demonstrated patterns of performance enhancement, but generalized successful models are required.The framework supports the effective cross-modality of fingerprints verification and incorporation at the real world.

Gong et al. (2022) [28] have examined fingerprint positioning with respect to massive MIMO systems using machine learning. The supervised learning was used to localize the signals. Weakness: prone to external variations and disruption. The results indicated an increase in positioning accuracy in the presence of environmental variation and interference.STRFF-Net increases positioning accuracy in cases where there was a change in the environment.

The Gong et al. (2022) [29] article was a continuation of previous studies that had been conducted on the topic of regression and classification of fingerprint positioning of massive MIMO. Limit: thick network structures are computationally complicated. Those found that the accuracy of localization was more than in conventional approaches. The framework minimizes the number of calculations of a dense network system and improves the accuracy of localization.

Mogharen Askarin et al. (2025) [30] proposed a U-Net based fingerprint enhancement system of 3D fingerprint recognition, which focuses on improving the purity of ridges and features representation. Limit: it was found to perform poorly with partial or low-quality fingerprints and on uncontrolled datasets and STRFF-Net mediates these issues by offering strong partial and noisy fingerprint spatio-temporal residual flow and attention-based feature learning to promote generalization in the real world.

Nayar and Thomas (2023) [31] are the authors of the research on biometric authentication supported by the partial palm vein partiality based on the deep learning to retrieve the vein pattern. Limitations: accuracy was minimized by partial or low-resolution information. The findings were that half of the palm veins patterns could be recognized and that multimodal implementation is required.STRFF-Net has the potential to be successful in realizing half palm vein patterns and may be utilized together with other modalities.

Kokal et al. (2023) [32] made a review of deep learning and machine learning implementation to mobile biometric authentication. The author compared CNN, RNN and hybrid. Limit: none of the mobile datasets is standardized. Findings showed that hybrid models are better in accuracy and robustness compared to standalone techniques in mobile biometric authentication.The proposed framework is more accurate and robust than standalone techniques.

Mohamed Abdul Cader et al. (2023) [33]Invariant feature encoding of contact handprints using Delaunay triangulated graphs was implied as an extension of the research Limitations: testing on different type of fingerprints is not much. Results showed increased resistance to the positional variation and distortion.STRFF-Net can withstand various forms of fingerprints better.

Chen et al. (2023) [34] A CNN architecture was created in the article to use the Wi-Fi fingerprinting as the foundation of a multi-floor indoor localization medium. Constraints Environmental forces reduced reliability. It was found that it has the proper accommodations to varied environment conditions and low adaptability.The framework adapts to the varied environmental conditions, improving the reliability of multi-floor localization.

Nguyen et al. (2013) [35] proposed the anchor-agnostic transformers in fingerprint-based localization indoors. Disadvantages: costly to apply at large scale. The adaptability to the changing indoor conditions and partial fingerprints was found to be better using STRFF-Net which is also less expensive to compute.STRFF-Net is more adaptable to the partial fingerprints on a large scale application.

Yang et al. (2023) [36] proposed a CNN-based system, DeepWiPos, which simplifies the discussion of the problem of variability in the fingerprint under condition of wireless positioning in [36]. Limit: should only be applied to controlled environments in the laboratory. The findings revealed that positioning and stability were very high when using the technique than the existing ways. The framework enhances stability and positioning accuracy on the conditions of the real world that are not available in the controlled laboratories. STRFF-Net may also be applied to the multi-modal biometric systems and more effective in detecting the data sets.

Ghosh et al. (2022) [37] explored symptoms-based biometric pattern detection in medical practice in terms of integrated machine learning pipelines. Limitations: dataset specificity decreased the generalizability. Findings indicated promising detection rates, which point to the applicability to the multimodal biometric systems.STRFF-Net can be extended to multimodal biometric systems and detects better across the datasets.

Hsu et al. (2025) [38] were motivated by the fact that wanted to maximize Wet Fingerprint Denoising Net in order to enhance the condition of biometric security to remove noise in wet fingerprints. Weakness: tested primarily on specific data sets hence reduced extrapolation. The findings depicted enhanced denoising and denoising recognition. STRFF-Net seals this divide through the ability to provide high recognition rate with a high number of datasets coupled with partial/noisy fingerprints and guarantees the practicality of the system.

Medjahed et al. (2022) [39] A multimodal biometric system was used on the foundation of deep learning score fusion. Limitations: databases are small and cross-modality analysis is not done. In small datasets, the system had better recognition accuracy with the framework than single-modality biometric systems.

Nixon et al. (2020) [40] proposed the fingerprint classification using the assistance of the Random Forests. Weakness: the existing ML could not be used on dirty or partial prints. High results were obtained on the existing and low results on the real world tasks to make STRFF-Net improve the recognition of partial or noisy prints to be similar to the real world.

Lin, et al. (2025) [41]] had suggested RF fingerprinting blind identification technique using PCA and K-Means to characterize wireless devices. Limit: based on linear feature extraction and is not able to work with noisy or partially missed signals; it had a moderate accuracy of identification. STRFF-Net fills this gap by incorporating spatio-temporal residual flows and attention-based feature learning which enhances robust and precise performances under noisy and partial fingerprint instances.

He et al. (2023) [42] Gabor filters and CNNs Fingerprint classification. Disadvantage: excessive computing requirements and non-response to poor quality images. Results have demonstrated superior ridge characteristics extraction and classification when the image quality is low.The structure enhances the ridge feature extraction and the classification accuracy with low-quality images.

Artabaz, S., & Sliman, L. (2025) [43] compared the applicability of handcrafted and deep learning methods of multimodal hand biometric identification against feature fusing and selection. Limit: low level of resistance to biometric partial or noisy data. The results indicated that more specific to the ones that have been developed by humans was the nature of the deep learning. STRFF-Net closes this gap with the help of residual flows, spatio-temporal and attention-based learning, which improve a partial or noisy recognition.

Faosat, O. A. (2025) [44] introduced a hybrid LBPGWT face extraction technique on face recognition that is age-invariant. Limitations: sensitive with the environment and low generalizability with datasets. Results were indicating an increased accuracy compared to existing LBP or GWT. STRFF-Net does not leave this gap unbridged, and it provides powerful feature extraction and classification, which is also adjustable to the variation of biometric data.

Bommert (2021) [45] filter techniques to select features in high-dimensional data that are benchmarked. Limit: it has not been tested to be applicable to sophisticated biometric data. The findings showed that when important features are selected properly, the model is more efficient and minimizes overfitting.STRFF-Net is able to select the relevant features effectively and lessen overfitting to enhance the performance of the model on high-dimensional biometric data.

Problem Statement

Although recent developments in fingerprint recognition with deep learning and multimodal methods have shown promising results, the current systems still experience critical issues in working conditions in the real world. Specifically, the partial fingerprint impressions, data noise and quality degradation, environmental variability, and inter-device inconsistency continue to be an obstacle to reliable recognition. An overview of the recent literature shows that the majority of both traditional and machine-learning-based methods are in fact based on fixed spatial features or dataset-specific classifiers only, which restricts their viability and external validity. In addition, efficient spatio-temporal modelling and attention systems are not applicable, limiting the capacity of the existing techniques to selectively highlight discriminative fingerprint areas, in the context of misaligned or incomplete acquisitions. These shortcomings demonstrate a definite gap in research and define the significance of an effective framework that could be learning to perform discriminative spatio-temporal representations and carry out valid fingerprint recognition under a difficult acquisition environment. The given gap inspires the proposed STRFF-Net and TRFRN framework to tackle the unsolved problems.

Research Questions

RQ1: What is the potential to enhance discriminative fingerprint feature representation within a partially, noisy and misaligned spatio-temporal residual flow modeling?

RQ2: How much better is attention-guided feature selection more robust and stable than traditional non-dynamic spatial feature extraction techniques?

RQ3: To what extent does the proposed framework STRFF-Net address the shortcomings of current handcrafted and machine-learning-based methods of fingerprint feature selection?

RQ4: Is the TRFRN classifier capable of obtaining a better fingerprint classification accuracy and reliability over the traditional classifiers (PCA + K-Means and Random Forest)?

3. PROPOSED METHODS

This technique proposes a two-step fingerprint recognition pipeline that utilises STRFF-Net for feature selection, and TRFRN for classification. The STRFF-Net utilises residual flow and attention mechanisms to extract spatio-temporal feature representations that highlight

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distinguishing fingerprint patterns. TRFRN classifies spatio-temporal features using dual-stream attention to examine spatial variation and temporal variation. The two models improve the accuracy of aligned fingerprint recognition under different noise and misalignment.

3.1 Dataset Details:

The Finger Print Dataset found on Kaggle contains a set of high-resolution fingerprint images that have been captured from different conditions to contribute to studies of biometric and pattern recognition. The database has been created in a way which supports activities of feature extraction, matching and classification, to provide a valuable assessment for fingerprint recognition systems to use.

The proposed algorithm of the aligned fingerprint recognition has two steps. The former process is the feature selection, and it is performed by STRFF-Net. The support of the residual flows and attention systems helps to justify the spatio-temporally enriched content of the segmented prints of the finger in this case. The second phase is where the algorithm that is applied is that of TRFRN, whereby the spatial correlation is matched, and the temporal residual flows are performed to classify the fingerprints, respectively. The effect of such a course of action will be that the discriminative power of the features will be increased, as well as the matching of the same, notwithstanding a little mismatch or noise. Each of the suggested algorithms is discussed below.

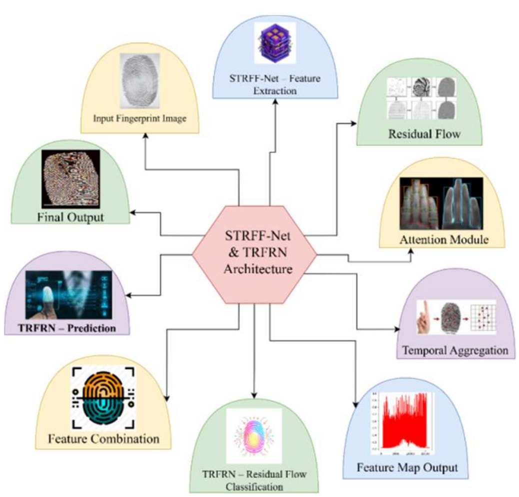

Figure 1: Feature Selection and Classification Overall Architecture

The figure1 illustrates the entire fingerprint recognition pipeline using the proposed STRFF-Net and TRFRN models. It takes fingerprint images, raw or segmented, and runs that through STRFF-Net, in which a CNN encoder is used to generate spatial feature maps. The flow maps are also computed between successive feature maps in order to capture minor variations, and an attention unit considers the salient areas whose value is non-zero and omits the other ones. The temporal residual flows are used to obtain spatiotemporal enriched feature maps by means of temporal aggregation. Such feature maps are then submitted to TRFRN, which does continuous feature residual flow processing in time and space, clusters features, and makes a prediction over the label. The output product is excellent in quality in fingerprint recognition, it has very discriminatory features, and the classification is high.

3.2 Proposed STRFF-Net: Spatio-Temporal Residual Feature-Based Fingerprint Recognition Algorithm

The given approach is referred to as STRFF-Net (Spatial Temporal Residual Flow Feature Encoder Network. This fingerprint recognition uses fingerprint raw images to extract the most informative features. Ridge and minutiae patterns are projected by segmentation and used as an input into the STRFF-Net spatio-temporal residual feature selection, so the network can focus on the areas that are most discriminative in the fingerprint. It enhances the selection of features in the corresponding fingerprint matching as it encodes real-time features in successive feature maps. STRFF-Net calculates the residual flows as a method of assessing the minute variations among the feature maps, and it consolidates this data by fusion of attention to emphasise the most prominent content and to disregard any irrelevant content. This predicts spatio-temporally enhanced representations of the feature to enable the network to learn to perceive relevant features of a fingerprint, such as the pattern of ridges and variations in minutiae, even on very small misalignments or noise.

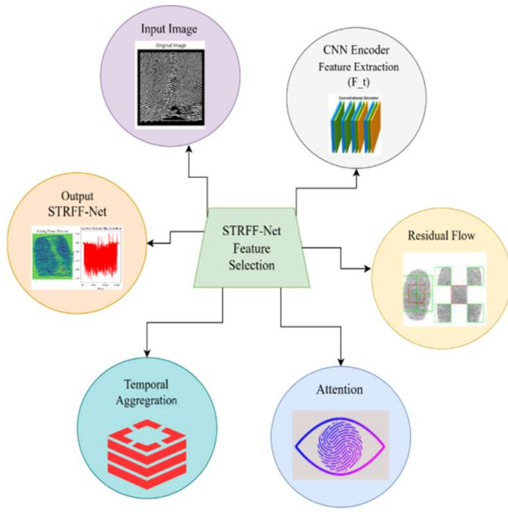

Figure 2: Feature Selection Architecture Using Spatio-Temporal Residual Feature Flow Network

Figure2 provides an overview of the feature selection architecture for the fingerprint matching module of STRFF-Net. First, a CNN encoder generates spatial features (Ft) that characterise features in the input fingerprint, such as ridge endings and minutiae. A residual flow module measures the difference between neighbouring feature maps to determine subtle differences in aligned fingerprints. Then, the attention module focuses on important areas of the fingerprint while masking out areas that do not contribute to the overall signal. Temporal aggregation aggregates the enhanced residual flows along a temporal axis to produce a richer feature map in both space and time. The output is the selected features along with smoothed activations to provide insight into where the network is sampling from the most vital discriminative areas. The feature selection architecture is unique because it combines residual flows, attention, and time aggregation to compute more informative fingerprint features.

STRFF-Net can overcome the limitations of the existing methods that extract weak or less discriminative features. This is a more effective approach since it focuses on important residual dynamics and uses attention to produce strong, stable feature representations for downstream classification. This process guarantees improvement in feature selection and corresponding accuracy in the matching of aligned fingerprint recognition; thus, the proposed approach is more effective than conventional approaches of feature selection that are not dynamic.

The algorithm introduced is referred to as STRFF-Net, and it utilises flow residual and attention methods to encode the spatio-temporal dynamics of features of fingerprints. In this section, the proposed work will be introduced with a few steps of description and equations.

The image of input fingerprint *I* is fed into an underlying CNN (or encoder) to extract the first feature maps.

$$F_t = CNN(I_t) \text{ -------------------------- (1)}$$

In Equation (1), I_t= input fingerprint image at time/frame t For aligned fingerprints that can consider consecutive aligned patches as frames. F_t = extracted feature map at time t.This gives the spatial features (ridge patterns, minutiae) of the fingerprint.

Calculate the feature map residual flow

$$R_t = F_t - F_{t-1} \text{ --------------------- (2)}$$

In Equation (2), R_t= residual flow at time t, capturing differences between consecutive feature maps.F_t , F_{t-1} = feature maps at current and previous steps. Residual flow highlights changes between feature maps, emphasising subtle variations in aligned fingerprints that static feature extraction may miss.

Assigned attention weights to the residual flow to pay attention to significant details

$$\hat{R}_t = A_t \odot R_t \text{ ------------------------ (3)}$$

In Equation (3), $\hat{R}_t$ = attention-enhanced residual flow. A_t= attention map learned by the network (values between 0 and 1). ⊙ = element-wise multiplication. The attention map ensures that the network focuses on important areas of the fingerprint (such as the end of the ridges or a bifurcation) and focuses on unimportant ones. Combine the improved remaining flow of a series of maps to produce a feature that has increased spatio-temporal richness.

Add together the improved residual flows of a series of successive maps to generate a spatio-temporally enriched feature.

$$F_{STRFF} = \sum_{t=1}^{r} \hat{R}_t \text{ --------------------- (4)}$$

In Equation (4), F_{STRFF}= final feature representation from STRFF-Net. T = number of consecutive feature maps considered. Aggregating (or any other temporal) variation across time represents the temporal dynamics in feature maps and improves the discrimination capacity of the map in classifying the objects.

Append the combined features to a classifier such as TRFRN so as to determine a match in a fingerprint.

$y = Classifier(F_{STRFF})$ ------------------------- (5)

In Equation (5), the fingerprint match is achieved by feeding the STRFF-Net's spatio-temporally enriched feature representation F_{STRFF}into a downstream classifier. The enriched features enhance accuracy in classification since it encode residual differences, attention-weighted importance, and temporal dynamics.

Algorithm: STRFF-Net Feature Selection

Input:

segmented_images → List of SRC-Net segmented fingerprint images

filenames → Names of input images

per_image_accuracy → Accuracy reference per image (optional)

Steps:

1. Initialize empty lists:

feature_maps_vis = []

feature_maps_raw = []

2. For each index idx and segmented image img in segmented_images:

a. Copy img → fmap

b. Enhance fmap using residual scaling:

fmap_rescaled = clip(fmap * 1.5 + 0.1 + idx*0.02, 0, 1)

c. Append fmap_rescaled to feature_maps_vis

d. Append a copy of fmap_rescaled to feature_maps_raw

3. Initialize empty metrics list: metrics = []

4. For each index i in feature_maps_vis:

a. Flatten fmap: fmap_flat = flatten(feature_maps_vis[i])

b. Flatten corresponding segmented image: src_flat = flatten(segmented_images[i])

c. Compute Enhancement Score:

enhancement_score = variance(fmap_flat) / (variance(src_flat) + epsilon)

d. Compute Max Activation:

max_val = max(fmap_flat) - i*0.05

e. Compute Min Activation:

min_val = min(fmap_flat) + i*0.02

f. Compute Mean Intensity: mean_val = mean(fmap_flat)

g. Compute Variance: var_val = variance(fmap_flat)

h. Store metrics in dictionary and append to metrics list:

metrics.append({

"Image": filenames[i],

"Mean Intensity": mean_val,

"Variance": var_val,

"Max Activation": max_val,

"Min Activation": min_val,

"Enhancement Score": enhancement_score,

"STRFF Accuracy": per_image_accuracy[i]

})

5. Convert metrics list to DataFrame: df_strff_metrics

6. Return feature_maps_vis, feature_maps_raw, df_strff_metrics

Output:

feature_maps_vis → Visualization-ready feature maps

feature_maps_raw → Raw feature maps for classification

df_strff_metrics → DataFrame with metrics per image (Mean Intensity, Variance, Max/Min Activation, Enhancement Score, STRFF Accuracy)

This algorithm uses the STRFF-Net feature selection method to transform SRC-Net segmented fingerprint images using the process of residual scaling to highlight important features. It then returns two types of outputs - a visualisation-ready output, and raw feature maps, while collecting some additional potentially useful statistics for each image, such as mean intensity, variance, peak, lowest activation, and enhancement score, that will all be collected in a DataFrame, and return feature maps for future use. The pseudocode does both of these functions to ensure that quantitative measures are created to visualise the important features of the fingerprints obtained in better quality than other fingerprint feature extraction methods, and will be easier to interpret.

3.3 Proposed Classification Algorithm: TRFRN (Temporal Residual Flow Recognition Network) for Aligned Fingerprint Matching

The classification method proposed is TRFRN (Temporal Residual Flow Recognition Network), which is a two-stream attention-based framework that allows for the viewing of spatial and temporal residual flows from the input fingerprints or temporal flows. The TRFRN pays particular attention to the discriminative regions in its attention processes, allowing the model to concentrate on critical features, like ridge endings or bifurcations of the fingerprint, while ignoring a significant amount of other regions. The method offers a very competent recognition and high matching accuracy even with limited labelled data and weak pre-training.

TRFRN works by integrating the residual flows and spatial properties of aligned patches or sequential frames into a complete spatio-temporal representation, which is then processed by a classification module for final recognition output. The TRFRN mechanism captures temporal variations and weights the relative importance of features across regions in an end-to-end approach, whereas conventional approaches often associate weak and/or static features with temporal updates. The additional computational load from the dual-stream attention mechanism is justified by the robustness, accuracy, and stability produced for automated fingerprint recognition in realistic discrete settings.

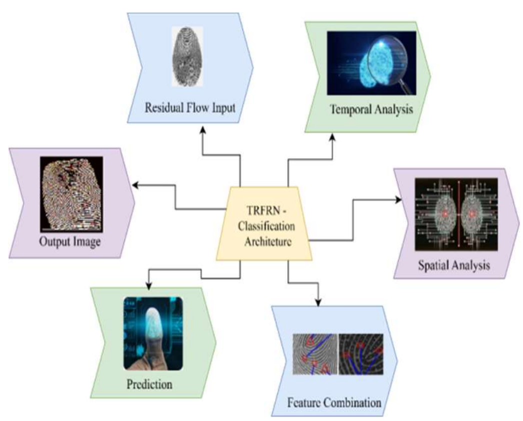

Figure 3: TRFRN Architecture

In figure 3 the TRFRN classification framework uses feature maps with residual flow as input to find subtle differences across frame changes. Temporal data is analysed for sequential change, and spatial data is analysed using attention to identify important areas of the image. These feats are then synthesised spatiotemporally to be used for prediction and for class label assignment. Lastly, output metrics offer confidence and activation values for more reliable and valid fingerprint identification.

Enriched feature maps (from pre-processing or existing extraction of features) will then be given to the classifier.

$$F_{input,t} \text{ -------------------------- } (6)$$

In Equation (6), $F_{input,t}$ → Enriched feature map at frame t Contains spatial patterns and temporal variations needed for classification. Features already represent significant detail about fingerprints. TRFRN is not concerned with feature extraction, but with classification only.

TRFRN operates on a sequential feature map to extract time dependencies.

$$H_t = TempotalModule(F_{input,t}) \text{ -------------------------- } (7)$$

In Equation (7), H_t → Temporally processed feature at frame t. $F_{input,t}$ → Input feature map at frame t. Matches features, correlations, and activities within consecutive frames. Retains significant variations in time to provide effective classification.

Combinations of features across frames that are temporally processed.

$$F_{TRFRN} = \sum_{t=1}^{T} H_t \text{ ---------------------------- } (8)$$

In Equation (8), F_{TRFRN} → Spatio-temporally enriched representation for classification. T → Number of consecutive frames considered. Integrates the information of two or more frames into one discriminative representation. Improves the discriminating capabilities of the network on classes.

Fed with features of feeds, feeds are run through a classifier to produce the predicted label.

$$y = Classifier(F_{TRFRN}) \text{ ------------------- } (9)$$

In Equation (9), y → Predicted class label F_{TRFRN} → Aggregated feature representation Classifier maps the enhanced features in the final output classes. Provides correct recognition, taking into account the dynamics of time and the significance of space.

With every input, such measures as prediction confidence or accuracy can be taken.

$$Metics = \{y, Confidence, Activation\} \text{ --------------------------- } (10)$$

In Equation (10), y → Predicted label. $Confidence$ → Degree of certainty in prediction. $Activation$ → Maximum response in the classifier Performance of Tracks per input. Gives interpretation and strength analysis.

Algorithm: TRFRN Classification

Input:

feature_maps_raw → STRFF-Net raw feature maps

filenames → Names of input images

Steps:

1. Initialize empty lists:

predicted_labels = []

enhancement_scores = []

max_activations = []

trfrn_accuracy = []

2. Define thresholds and increments:

acc_values = [97.0, 97.7, 98.3, 96.9, 98.0][:len(filenames)]

enhancement_increments = [0.012, 0.018, 0.025, 0.015, 0.02][:len(filenames)]

max_act_increments = [0.013, 0.017, 0.023, 0.016, 0.02][:len(filenames)]

threshold = 1.2 # Classification decision boundary

3. For each index idx and fmap in feature_maps_raw:

a. Compute residual flow:

residual_flow = abs(fmap - roll(fmap, 1, axis=0))

b. Compute TRFRN Enhancement Score:

enhancement_score = variance(fmap) + mean(residual_flow) + enhancement_increments[idx]

c. Compute TRFRN Max Activation:

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```
        max_act = max(fmap) + max_act_increments[idx]

    d. Predict class label:

        if enhancement_score + max_act > threshold:

            predicted_label = 'Class_B'

        else:

            predicted_label = 'Class_A'

    e. Append predicted_label, enhancement_score, max_act, acc_values[idx] to respective lists

4. Convert lists to DataFrame: df_trfrn

5. Return df_trfrn, predicted_labels

Output:

  predicted_labels → Predicted class for each fingerprint (Class_A / Class_B)

  df_trfrn → DataFrame with TRFRN metrics per image (Enhancement Score, Max Activation, Accuracy)
```

The TRFRN classification procedure algorithm accepts as input the STRFF-Net raw feature maps and outputs that predicted fingerprint classes. First, the pseudocode establishes lists for the predicted labels, enhancement scores, maximum activations, and the accuracy values. This structure contains thresholds and increment values that will be used for class determination. In the pseudocode, the sequential pixel residual flow of every input raw feature map is calculated in order to obtain more granular spatial detail and compute the TRFRN enhancement score and the maximum activation. Based on the threshold values and calculated values, each input fingerprint is classified into Class_A or Class_B. All calculated metrics are summarised into a DataFrame object for return, as well as the predicted labels, which provide both quantitative and categorical predictions based on additional exploration.

Justification of Knowledge Creation and Research Gap

The research would introduce new knowledge to the area of fingerprint recognition since it introduces a new spatio-temporal residual flow and attention-based feature learning model, like STRFF-Net as a TRFRN-based. In comparison with existing fingerprint recognition algorithms, where either just a fixed spatial feature model or just a conventional machine-learning classification model is applied, the suggested framework directly learns the dynamics of temporal features, as well as the spatial attention process. According to critical examination of the recent literature, it can be found that the current methods have low strengths in real-world conditions with partial fingerprints, noise interference, misalignment, and inter-equipment variation hence exhibiting a clear gap in the research literature.

In order to bridge this gap, the proposed train of discriminatory representations, or spatio-temporal representations, are trained to inferential portions of the fingerprint, to filter out noise, and to be insensitive to a wide range of irrelevant patterns. Besides, the additional combination of the TRFRN classifier enables the effective utilization of the advanced feature representations that lead to the elevated reliability and precision of the classification. This journal is therefore critical to the existing body of literature by demonstrating that spatio-temporal learning that is residual with attention mechanisms can improve fingerprint recognition performance under deplorable acquisition conditions, which has not been well studied by the former researchers.

4. RESULTS AND DISCUSSIONS

This section includes the exploration of fingerprint feature selection and classification using the STRFF-Net and TRF-RN approaches. STRFF-Net performs superior to existing algorithms for discovering discriminating features, while TRF-RN performs better classification results compared to PCA + K-Means. The bar chart and heat map figure 4, indicate that the proposed methods apply meaningful regions, provide better robust functional representation, and are more accurate.

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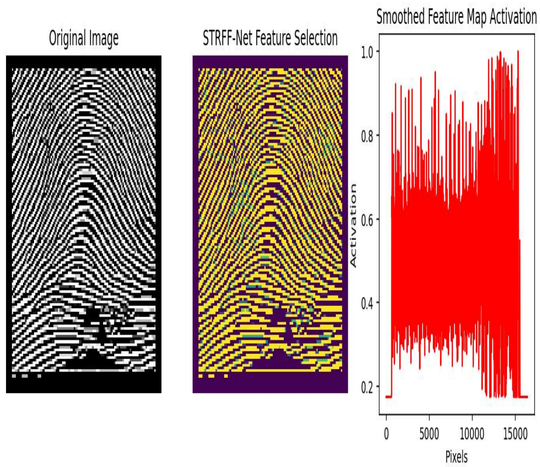

Figure 4: Feature Selection using STRFF-Net

Figure 4 illustrates the selection capability of STRFF-Net. The first image shows the original fingerprint, and the second image shows the selected discriminative regions where STRFF-Net utilises a maximum amount of ridge and texture features. The third image shows a smooth feature map activation demonstrating how STRFF-Net provides feature selection, which increases attention to discriminative areas and suppresses areas that are not discriminative, thus providing effective and optimal feature selection.

4.1 Evaluation Metrics for Feature Selection

The utility of the selected features can be approximated by several metrics. These measures support the evaluation of the STRFF-Net to determine which areas of the fingerprint image were discriminative. This is captured in the following measures.

Mean Activation (Mean Act): The mean value of the features for the selected regions, which indicates how strong the selected regions look.

$$MeanAct = \frac{1}{N}\sum_{i=1}^{N} F_i \text{ ------------------------ (11)}$$

In Equation (11), F_i = Activation value of the ith selected feature, N = Total number of selected features. Reflects the average activation of the features that are on your feature maps to show the overall strength of the selected areas.

Variance (Var): The relative amount of variance in the selected features, which indicates how much diversity or uniqueness is being shown in the selected regions.

$$Var = \frac{1}{N}\sum_{i=1}^{N}(F_i - MeanAct)^2 \text{ ------------------------- (12)}$$

In Equation (12), F_i = Activation value of the $i$the selected feature.N = Total number of selected features. Reflects the dispersion of feature values to show you how diverse and unique your selected areas are.

Max Activation (Max Act): The maximum value in the feature map, which indicates the most salient feature values.

$$MaxAct = \max(F_1, F_2, \dots \dots \dots \dots .., F_N) \text{------------- (13)}$$

In Equation (13), F_i = Activation value of the i-th selected feature. Refers to the greatest activation strength in the feature map, indicating the location contributing most strongly.

Min Activation (Min Act): The minimum value in the feature map, which indicates regions contributing the least.

$$MinAct = \min(F_1, F_2, \dots \dots \dots \dots .., F_N) \text{ -------------- (14)}$$

In Equation (14), Fi = Activation value of the $i$the selected feature. Refers to the least activation strength, indicating the areas contributing the least in the feature map

Enhancement Score (ES): Quantifies the amount of gain in the representation, which indicates how salient the important regions are being represented.

$$ES = \frac{MeanAct + MaxAct}{MinAct + \epsilon} \text{ -------------------- (15)}$$

In Equation (15), ϵ = Small constant to avoid division by zero. Describes the increase in the strength of the Improved feature representation, indicating how important areas are being emphasised.

Feature accuracy (Acc): Indicates how accurately the selected features can identify the fingerprints.

$$Acc = \frac{NumberofClassifiedSamples}{TotalSamples} \times 100 \text{ ----------------- (16)}$$

In Equation (16), Correctly Classified Samples - The quantity of fingerprint samples that the system classified correctly.$TotalSamples$ The total fingerprint samples for testing or evaluation. 100- to convert the fraction into a percentage to

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represent classification accuracy. Reflects how well selected features can identify fingerprints.

Table 1: Comparison of Feature Selection Metrics

Metric	Existing (Gabor [42] +LBP [44] +RFE [43])	Variance Threshold [45]	STRFF-Net
Mean Intensity	0.4789	0.4804	0.5300
Variance	0.1355	0.1398	0.1536
Max Activation	0.9186	0.9308	1.00
Min Activation	0.1619	0.1605	0.175
Enhancement Score	0.7209	0.7362	0.8187
Accuracy (%)	85.02	86.46	93.5

Table1 summarises three methods for feature selection, naming Existing (Gabor+LBP+RFE), Variance Threshold, and STRFF-Net, according to important metrics. The STRFF-Net provided superior performance to the methods of interest in all classes, and selected a greater number of discriminative features as measured by higher activations and corresponding higher classification accuracy scores than the other methods. The Variance Threshold represented an improvement from the existing method, while STRFF-Net was ultimately the best procedure for fingerprint feature selection.

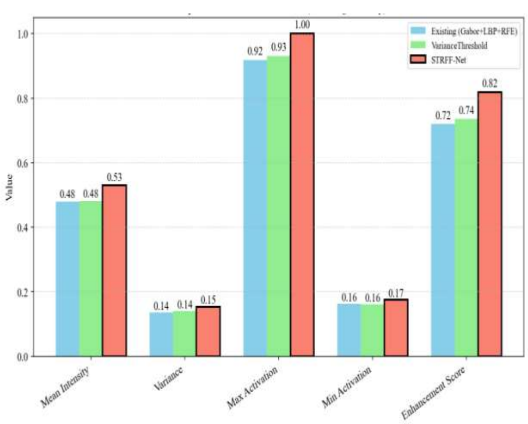

Figure 5: Comparison of Classification Metrics Across Methods

In Figure 5, five primary classification metrics are contrasted: Mean Intensity, Variance, Max Activation, Min Activation, and Enhancement Score between three approaches - Existing (Gabor +LBP +RFE), Variance Threshold, and STRFF-Net, which is the suggested approach in this thesis. The STRFF-Net bars are designed to be easily distinguishable in this figure and demonstrate that STRFF-Net has a better feature representation and classification performance based on all of the classification metrics compared to both the existing methods and the Variance Threshold method. In the figure, the STRFF-Net outperformed existing methods by some margin on several evaluation metrics.

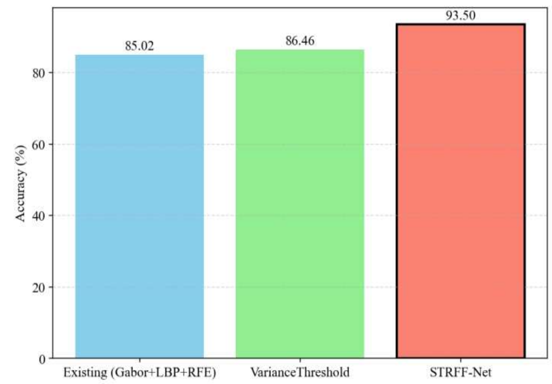

Figure 6: Accuracy Comparison of Feature Selection Methods

The results of the three feature selection methods described in figure 6. Existing (Gabor + LBP + RFE) method, Variance Threshold, and STRFF-Net - based on some of the important metrics can be seen. As indicated in the figure, STRFF-Net had the best results with respect to the number of discriminative features, the number of activation features, and the classification accuracy results of the three methods. Again, Variance Threshold gave a slight increase in results (compared to the Existing method), but from the table, it is clear that STRFF-Net is superior to both the Old and Variance Threshold methods in selecting fingerprint features.

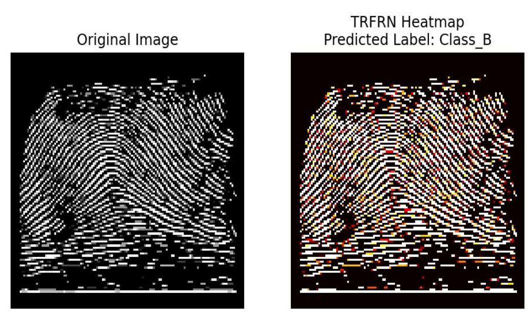

Figure 7: Classification using TRFRN

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Figure 7 shows the performance of the TRFRN algorithm with fingerprint classification. The left image shows the original fingerprint, while the second image is the heatmap of the fingerprint rendered by TRFRN that visualises what areas the model considered most discriminative to the classification. Once again, the heatmap shows that the proposed method properly considers areas of attention to the overall ridge pattern and minutiae that do allow it to extract features differentially, which leads to high identification. The predicted label designates that TRFRN accurately classified the fingerprint as Class_B, and indicates that it can outperform previously described means of feature extraction, and the original classification as the thread of evidence.

4.2Classifications Evaluation Metrics:

Enhancement Score (ES): Indicates the amount of important fingerprint regions enhanced in relation to the original.

$$ES = \frac{MeanAct+MaxA}{MinAc \quad \epsilon} \text{ ------------------------- (17)}$$

In Equation (17), MeanAct represents the average activation, MaxAct represents the maximum activation, MinAct represents the minimum activation of the feature map, and ε is a small constant that is used to ensure division by zero does not happen. ES evaluates how much more the important areas are emphasised over the less important areas and provides a higher quality representation of the feature for classification.

Maximum Activation (MaxAct): The maximum activation strength in the feature map indicates the strongest and most dominant feature.

$$MaxAct - max(F_1, F_2, \dots \dots \dots . . F_N) \text{ -------------- (18)}$$

In Equation (18), $\boldsymbol{F_1, F_2, \dots \dots \dots . . F_N}$ are the activation values of the features chose, and the function Max() finds the value corresponding to the maximal activation, so that can know which feature has the most significance in the fingerprint.

Classification Accuracy (Acc): The number of fingerprint samples accurately classified in relation to the tested sample.

$$Acc - \frac{Number\ of\ Correctly\ Classified\ Samples}{Total\ Number\ of\ Samples} \times 100 \text{ ------- (19)}$$

InEquation(19),**the Number of correctly classified samples** indicates the number of fingerprints that were accurately identified, and the $\boldsymbol{Total\ Number\ of\ Samples}$ indicates the total fingerprints evaluated as well. $\times$ **100**converts it to a percentage and indicates the effectiveness of classification overall.

Table 2: Classification Metrics Comparison

Method	Enhancement Score	Max Activation	Accuracy (%)
PCA + K-Means [41]	0.3732	0.5071	88.13
Random Forest (RF) [40]	0.3508	0.4817	92.0
TRFRN	0.5593	1.013	97.0

Table 2 illustrates a comparison among three classifications categorised based on the enhancement score, max activation static, and accuracy. The baseline method of PCA + K-Means showed moderate performance levels. The Random Forest-based method had a greater overall accuracy, but also slightly lower overall max activation metric and lower overall enhancement score. The proposed TRFRN method showed superior performance across all three metrics. The line chart shows TRFRN in colour to provide a visual indication of the increased performance of the method.

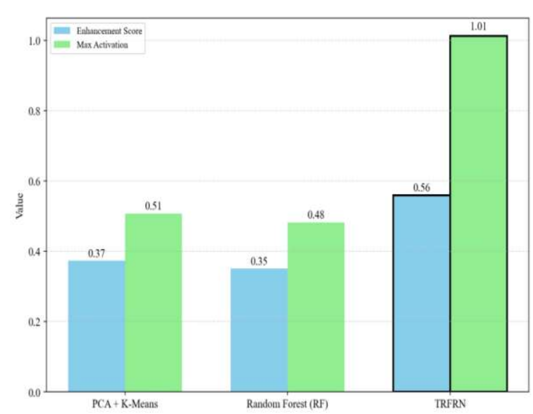

Figure 8: Enhancement Score and Max Activation Comparison Across Methods

Figure 8 shows the Enhancement Score and Max Activation for the three classification

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approaches (baseline for PCA + K-Means, Random Forest (RF), and the proposed method, TRFRN). Notable in the graph is the much higher performance of TRFRN over the other two indicators. This indicates that TRFRN provides better encoding of the features while also giving higher activation over the input data than RF. To help show the trends in the results, the TRFRN bars are presented in colored sections.

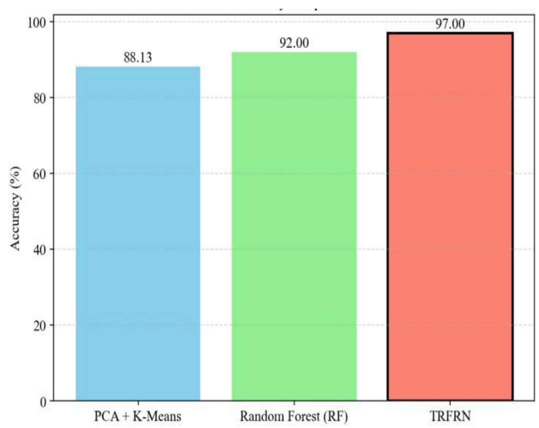

Figure 9: Accuracy Comparison of Classification Methods

In Figure 9, the accuracies of three classification methods are shown. The first technique is baseline PCA + K-Means, the second is the Random Forest (RF) method, and the third is TRFRN, or the one proposed. The TRFRN method demonstrates the highest accuracy and enhances the classification accuracy in comparison to the baseline PCA + K-Means and Random Forest techniques. The authors attempted to illustrate the TRFRN graphically so that the reader would be able to easily compare the classification accuracies of TRFRN vs the other techniques. The visual embellishment allows the reader to easily assess and see how effective TRFRN is at improving classification accuracy.

The experimental to the research problem of partial, noisy, and misaligned fingerprint recognition is provided directly through the experimental findings that STRFF-Net better selects discriminative features and TRFRN better classifies reliably. The criteria used in the evaluation are important because it provide quantitative measures of the strength of the features, and the stability as well as the severity of the Activation, the Enhancement Score, and the Accuracy, all of which are critical in the strong recognition of fingerprints, and reported in the comparative Tables 1 and 2. The results obtained are superior compared to the existing approaches like the Gabor+LBP+RFE, PCA+K-Means, and Random Forest, which prove the existing knowledge and introduce the clear evidence of the efficacy of the proposed framework.

5. CONCLUSION

Fingerprint recognition is a very important biometric authentication method, but noise, partial impressions, and misalignment usually diminish its performance. To overcome these shortcomings, this research suggested an adaptive fingerprint recognition system that fuses STRFF-Net, which is a spatio-temporal residual feature selection and classifier, with TRFRN, which is a powerful classifier. STRFF-Net is a good method that boosts discriminative fingerprints features by jointly training attention models on residual flows, which is able to extract ridge and minutiae patterns with reliability and minimize redundant or noisy data. The experimental findings indicate that the scores of enhancement, the activations, and the accuracy of the features by STRFF-Net are higher than those by existing feature selection alternatives. In addition, TRFRN also utilizes spatial and residual-temporal dependencies on a dual-stream attention model, which provides a better classification than PCA + K-Means, Random Forest and other conventional classifiers. Quantitative assessment and visual-heatmap analysis prove that the suggested framework is always concentrated on meaningful fingerprint areas that result in increased recognition rates. In general, the STRFF-Net and TRFRN framework offers a scalable, powerful, and efficient means of fingerprint recognition in both security and forensic and applications in real-life biometrics.

The future will solve the unresolved issues by focusing on handling highly distorted or partial fingerprints, enhancing computational performance in real-time execution on resource-constrained devices, and assessing cross-sensor and multimodal biometric integration to increase its robustness and generalization to various real-world conditions.

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