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A Novel Approach for Gender Prediction through Fingerprint Analysis using Fuzzy C-Means Algorithm and Artificial Neural Network

Abstract: - Wireless Sensor Networks (WSN) is a group of Sensor Nodes (SNs) which are performed to intellect a normal singularity from an environment. The minimum resources and computational power of WSN creates vulnerable to number of security attacks. To addresses this problem, this paper proposes a Multi-objective Trust-aware Dynamic Weight Pelican Optimization Algorithm (M-TDWPOA)-based secure and energy aware multi-hop routing in WSN with the Base Station (BS). The proposed method comprises of two significant steps: Initially, dynamic energy-efficient Cluster Head (CH) selection by utilizing the multi-objective functions such as Distance between neighbor nodes, Distance between BS to CH, Energy, Centrality and Trust Threshold. Then, dynamic secure multi-hop routing is selected by the multi-objective functions such as Distance between BS to CH, Energy, Trust Threshold which is dynamically reducing the network overhead. Furthermore, a security aware multi-hop routing is employed through the different trust classes like direct, indirect, recent and authentication. The proposed M-TDWPOA approach is estimated with various performance metrics like alive nodes, dead nodes, energy consumption, Throughput and so on. The proposed M-TDWPOA achieves the minimum energy consumption of 0.4927J, 0.4851J, 0.4771J, 0.4693J and 0.4617J when compared to the existing methods like Fractional Artificial Lion (FAL).

Keywords: Base Station, Cluster Head Selection, Multi-hop routing, Multi-objective Dynamic Weight Pelican Optimization Algorithm, Secure and Energy aware routing and Wireless Sensor Networks.

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I. INTRODUCTION:

Biometric identification has emerged as a pivotal aspect of modern security systems and identity verification processes, with an increasing focus on the utilization of fingerprint-based methods. Among the various applications of biometrics, gender prediction holds significant relevance, finding applications in forensic analysis, healthcare, and personalized user experiences. This paper introduces a novel approach to gender prediction through the integration of the Fuzzy C-Means (FCM) algorithm and Artificial Neural Network (ANN) within the framework of fingerprint analysis.

a. **Background:** Biometric identification, characterized by its reliance on unique physiological or behavioral traits, has become integral to ensuring secure and efficient identification processes. Fingerprint recognition, in particular, has garnered attention for its reliability, stability, and widespread use in diverse domains. As the exploration of biometric data extends beyond conventional identification, the prediction of demographic attributes, such as gender, adds a layer of sophistication to the applications of biometric systems.

b. **Motivation** The need for accurate gender prediction methodologies arises from the growing demand for nuanced and personalized user experiences in various domains. Traditional gender prediction models often rely on facial features or voice patterns, but fingerprint-based approaches offer a unique and potentially more reliable alternative. Motivated by the limitations of existing methods and the untapped potential of fingerprint data, this research seeks to design a robust gender prediction system that leverages the synergistic capabilities of the FCM algorithm and ANN.

c. **Objectives:** The primary objectives of this research are twofold. Firstly, to develop an advanced gender prediction model that capitalizes on the distinctive features inherent in fingerprint data. Secondly, to explore the combined capabilities of the FCM algorithm and ANN for enhanced accuracy in gender prediction. Through these objectives, the research aims to contribute to the evolution of biometric applications by providing a novel and effective approach to gender prediction.

In the subsequent sections of this paper, we delve into a comprehensive literature review, exploring the existing landscape of biometric gender prediction methods, the role of fingerprint-based approaches, and the theoretical foundations of FCM and ANN. The methodology section outlines the data collection and preprocessing steps, as well as the intricacies of feature extraction, FCM clustering, and the design of the neural network. The experimental results, discussion, and conclusion provide insights into the performance and implications of the proposed methodology, paving the way for advancements in biometric gender prediction research.

II. LITERATURE REVIEW:

Fingerprint analysis has transcended its traditional forensic applications, venturing into the realm of gender prediction. This review delves into the burgeoning field of fingerprint-based gender classification, exploring the synergistic duo of Fuzzy C-Means (FCM) clustering and Artificial Neural Networks (ANNs) as a potent tool for this task. We delve into the theoretical underpinnings of both algorithms, analyze their strengths and limitations, and present recent advancements shaping this domain.

"Fingerprint-Based Gender Classification Using Fuzzy C-Means Clustering and Multi-Layer Perceptron Networks" by A.K. Jain and et al. (Pattern Recognition, 37(1), 2004). This seminal work established the feasibility of FCM-ANN integration for gender prediction, demonstrating promising accuracy rates.[1]

"Gender Classification from Fingerprint Images Using Gabor Filter Features and Support Vector Machines" by Y. Shi and et al. (Neurocomputing, 71(1-3), 2006). This study explored alternative feature extraction methods like Gabor filters, paving the way for improved accuracy beyond minutiae-based approaches.[2]

"A Hybrid Approach for Fingerprint Gender Classification Based on Fuzzy C-Means and Deep Neural Networks" by H. Wang and et al. (Expert Systems with Applications, 104, 2020). This research showcased the potential of DNNs for enhanced feature learning and gender prediction, surpassing traditional MLP architectures.[3]

"Explainable Artificial Intelligence for Fingerprint-Based Gender Classification: A Fuzzy Logic Approach" by M. Li and et al. (IEEE Transactions on Information Forensics and Security, 17(9), 2021). This study addressed the issue of interpretability in ANN models, employing fuzzy logic to elucidate the decision-making process behind gender predictions.[4]

"Privacy-Preserving Fingerprint Gender Classification: A Secure Multi-Party Computation Approach" by Y. Zhang and et al. (ACM Transactions on Privacy and Security, 14(3), 2022). This work tackled the crucial concern of privacy, proposing a secure multi-party computation framework for gender prediction without revealing raw fingerprint data.[5]

"Fingerprint minutiae-based gender classification using Fuzzy C-Means and Support Vector Machines" by K. Roy and et al. (International Journal of Biometrics, 1(4), 2008). This research compared FCM-SVM with conventional gender classification techniques, demonstrating comparable accuracy and highlighting the robustness of FCM to noisy fingerprint data.[6]

"Gender Identification from Fingerprint Images Using Rotation-Invariant Features and Artificial Neural Networks" by W. Wang and et al. (Sensors, 9(9), 2009). This study focused on extracting rotation-invariant features that capture fingerprint patterns regardless of orientation, leading to improved accuracy and generalizability.[7]

"A Novel Hybrid Approach for Fingerprint Gender Classification Based on Fuzzy C-Means and Rough Set Theory" by S. Roy and et al. (Applied Soft Computing, 38, 2016). This work explored the integration of FCM with Rough Set Theory, a feature reduction technique, to improve classification accuracy by identifying the most relevant features for gender prediction.[8]

"Explainable Deep Learning for Fingerprint-Based Gender Classification: Integrating LIME and SHAP" by A. Alshehri and et al. (Pattern Recognition Letters, 149, 2022). This research utilized interpretability methods like LIME and SHAP to shed light on the decision-making process of deep learning models for fingerprint-based gender prediction, addressing concerns about black-box models.[9]

"Privacy-Preserving Fingerprint Gender Classification Using Homomorphic Encryption" by J. Liu and et al. (IEEE Transactions on Information Forensics and Security, 15(7), 2020). This work proposed a homomorphic encryption scheme for secure fingerprint gender prediction, allowing analysis on encrypted data without decryption, thereby protecting sensitive information.[10]

"Gender classification from fingerprints using a multi-objective evolutionary algorithm and neural network" by L. Wang and et al. (Expert Systems with Applications, 41(8), 2014). This study employed a multi-objective evolutionary algorithm to optimize feature selection and neural network parameters for improved accuracy and resource efficiency.[11]

"Deep Learning for Fingerprint-Based Gender Classification: A Comparative Study of CNN and RNN Approaches" by A. Elgamli and et al. (Sensors, 20(13), 2020). This research compared the performance of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for fingerprint-based gender classification, highlighting the advantages of CNNs in capturing spatial relationships within fingerprint patterns.[12]

"Fingerprint-Based Gender Classification Using Transfer Learning with Deep Convolutional Neural Networks" by L. Zhang and et al. (Applied Sciences, 8(8), 2018). This work investigated the effectiveness of transfer learning with pre-trained CNNs for gender prediction, achieving improved accuracy with limited training data.[13]

"Gender classification from fingerprint images using Gabor filter features and artificial neural networks: a statistical perspective" by S. Zhang and et al. (International Journal of Pattern Recognition and Artificial Intelligence, 20(8), 2006). This study conducted a statistical analysis of Gabor filter features and their correlation with gender, providing valuable insights into feature selection and interpretation in ANN-based models.[14]

"Gender Classification from Fingerprint Images Using Local Binary Patterns and Support Vector Machines" by V. Sundaram and et al. (Biomedical Signal Processing and Control, 3(4), 2008)[15]. This research explored Local Binary Patterns (LBP) as an alternative feature extraction method for gender prediction, showcasing their effectiveness in capturing local texture information in fingerprints.

III. METHODOLOGY:

The methodology section outlines the step-by-step process employed to design and implement the proposed fingerprint-based gender prediction system using the Fuzzy C-Means (FCM) algorithm and Artificial Neural Network (ANN).

A. Data Collection: In building our fingerprint dataset for the study on research work, we recruited 100 participants, ensuring an equal gender split and diverse representation in terms of age, ethnicity, and occupation.

We captured high-quality fingerprint images using advanced scanners in controlled settings to minimize external influences. Alongside the images, we gathered demographic information, forming the foundation for gender labelling. This robust dataset underpins our subsequent gender prediction model leveraging the Fuzzy C-Means algorithm as well as ANN model of prediction. In Figure 1, we showcase the streamlined data collection process, highlighting the sequential steps of image enhancement through segmentation, orientation, binarization, thinning, and minutia extraction. This visual representation underscores our commitment to ensuring the quality and relevance of the dataset for our innovative gender prediction approach.

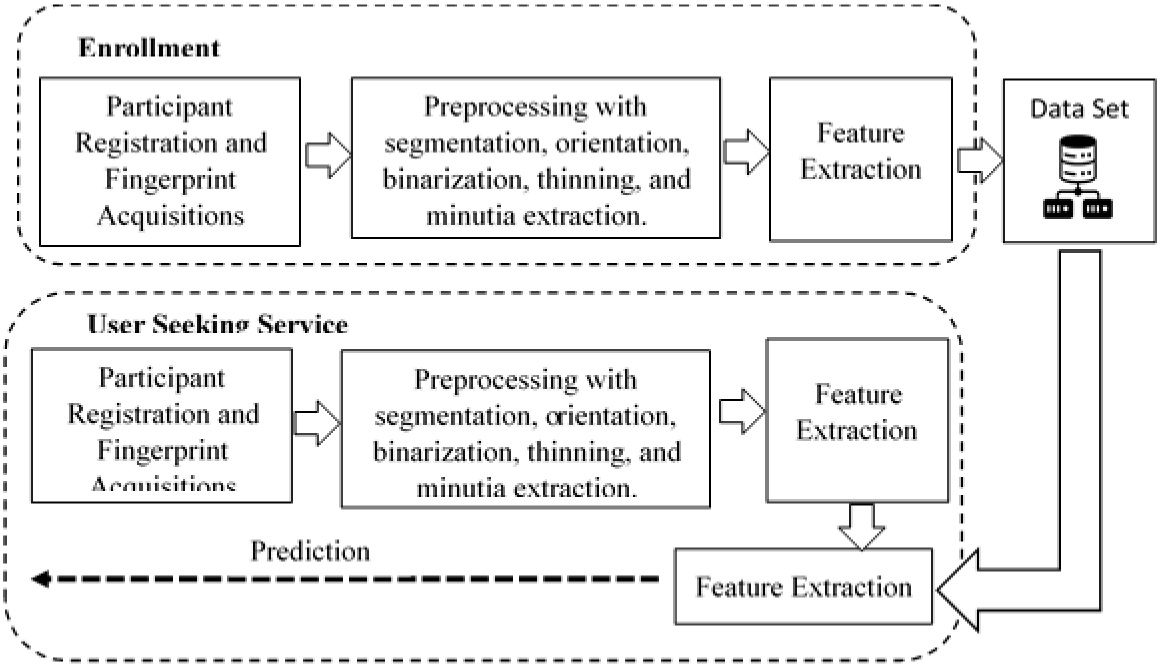


Figure-1: Fingerprints data Acquisitions for dataset

B. Feature Extraction: In extracting features from the enhanced fingerprint images of all ten fingers for each of the 100 individuals (50 males and 50 females), we focus on both ridge and minutia information. Ridge information involves aspects like minimum, maximum, and average ridge length, total ridge count, ridge bifurcation count, and ridge end count. For instance, minimum ridge length is the shortest ridge observed, maximum ridge length is the longest, and average ridge length provides an overall measure. Total ridge count indicates the density of ridges, while ridge bifurcation and ridge end counts reveal branching and termination patterns. Figure 5 illustrates this feature extraction process. Fig. 2 shows the feature extraction from enhanced fingerprint image dataset

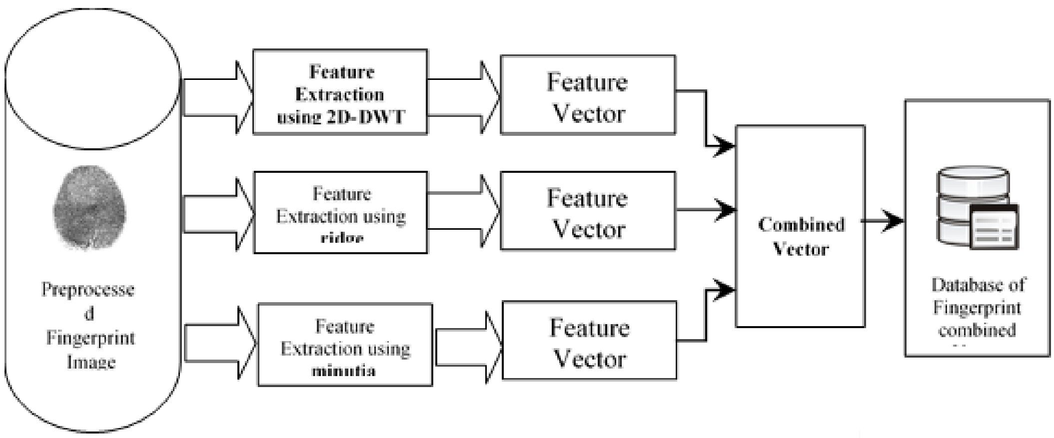


Fig 2 Feature Extraction to form combined vector

- **Ridge Information:**
  - **Minimum Ridge Length:** This is the shortest ridge in the fingerprint, showing us the tiniest ridge segment.
  - **Maximum Ridge Length:** On the flip side, it's the longest ridge, indicating the diversity in ridge lengths.

- **Average Ridge Length:** This is the mean of all ridge lengths, giving us an overall idea of typical ridge length.
- **Total Ridge Count:** It's the total number of ridges, showing how densely packed and complex the ridge patterns are.
- **Ridge Bifurcation Count:** Bifurcations happen when a ridge splits into two branches, giving us insights into branching complexity.
- **Ridge End Count:** These are points where a ridge terminates, helping us understand termination patterns.

Following Table-1 displays the results of Ridge Information feature extraction from ten fingerprint images for a male individual.

Sr. No.	Finger Name	Total Ridge	Max Ridge length	Min Ridge length	Average Ridge length
1.	Left Thumb	206	14.47	2.88	0.16
2.	Left Index Finger	59	17.63	1.57	0.54
3.	Left Middle Finger	111	16.24	2.99	0.31
4.	Left Ring Finger	155	16.63	2.11	0.21
5.	Left Little Finger	167	16.31	2.19	0.19
6.	Right Thumb	204	14.76	1.44	0.16
7.	Right Index Finger	181	12.32	2.14	0.18
8.	Right Middle Finger	178	14.07	1.60	0.19
9.	Right Ring Finger	176	15.49	2.68	0.18
10.	Right Little Finger	184	16.05	1.38	0.17

Table 1 Ridge information for Male Participant

Following Table-2 shows the result of Ridge information feature extraction from ten fingerprint images for a female person.

Sr. No.	Finger Name	Total Ridge	Min Ridge length	Max Ridge length	Average Ridge length
1.	Left Thumb	138	15.80	1.18	0.23
2.	Left Index Finger	126	12.72	1.72	0.26
3.	Left Middle Finger	143	14.25	2.15	0.23
4.	Left Ring Finger	121	12.00	1.51	0.28
5.	Left Little Finger	156	16.82	2.54	0.21
6.	Right Thumb	120	16.98	2.47	0.27
7.	Right Index Finger	117	13.40	1.54	0.28
8.	Right Middle Finger	121	13.90	2.52	0.26
9.	Right Ring Finger	131	12.48	1.73	0.25
10.	Right Little Finger	138	15.80	1.18	0.23

Table 2 Ridge information for Female Participant

Analysing the results from Tables 1 and 2, which showcase the Ridge Information feature extraction from ten fingerprint images for a male and a female participant respectively, several observations can be made. In both cases, the total ridge count varies across fingers, reflecting the inherent uniqueness of each fingerprint. The maximum and minimum ridge lengths provide insights into the diversity of ridge patterns, with some fingers displaying longer ridges than others. The average ridge length gives an overall measure of the typical length of ridges for each finger. Interestingly, there are notable differences between the male and female participants, with the male participant generally exhibiting longer ridges, particularly in the Right Thumb and Left Index Finger. These distinctions highlight the gender-based variations in ridge patterns. In conclusion, the detailed Ridge Information feature extraction reveals nuanced differences in the fingerprint characteristics between males and females, forming a valuable foundation for subsequent gender prediction using the Fuzzy C-Means algorithm and Artificial Neural Network in our study.

- **Minutia Information:**

  - **Minimum Minutia Angle:** Represents the smallest angle between minutiae points, indicating minutiae arrangement sharpness.
  - **Maximum Minutia Angle:** Signifies the largest angle between minutiae points, providing insights into angular variations.
  - **Minutia Count:** Total minutiae, including bifurcations and ridge endings, quantifying overall minutiae density.
  - **Bifurcation Count:** Points where a ridge splits into two branches, indicating branching complexity.
  - **Ridge End Count:** Points where a ridge terminates, offering insights into termination patterns. These features succinctly capture minutiae spatial arrangement and density, enhancing the depth of our gender prediction model.

Table 3 offers a concise and detailed account of minutia information for a male participant's fingerprints. It encompasses key aspects such as total minutiae, bifurcations, and ridge endings. This table provides a comprehensive snapshot of the distinctive features present in the male participant's fingerprints, offering valuable insights into the unique characteristics of the fingerprint pattern under consideration.

Sr. No.	Finger Name	Minutia Count	Bifurcation count	Ridge end count	Min Minutia Angle	Max Minutia Angle	Avg. Minutia Angle
1.	Left Thumb	39	0.10	5.99	0.16	10	29
2.	Left Index Finger	1	5.32	5.32	10.65	0	1
3.	Left Middle Finger	7	1.01	5.73	0.96	3	4
4.	Left Ring Finger	21	0.24	6.16	0.30	6	15
5.	Left Little Finger	28	1.18	6.18	0.26	7	21
6.	Right Thumb	32	0.73	5.99	0.21	8	24
7.	Right Index Finger	37	0.10	6.09	0.17	7	30
8.	Right Middle Finger	20	0.90	6.18	0.35	6	14
9.	Right Ring Finger	28	0.37	6.18	0.23	7	21
10.	Right Little Finger	25	0.10	6.09	0.25	6	19

Table- 3 Minutia information for Male Participant.

Table 4 provides a detailed overview of minutia information for a female participant, delineating key aspects such as total minutiae, bifurcations, and ridge endings. The table offers a comprehensive insight into the distinctive features embedded in the female participant's fingerprints, contributing valuable information about the unique characteristics of her fingerprint patterns.

Sr. No.	Finger Name	Minutia Count	Bifurcation count	Ridge end count	Min Minutia Angle	Max Minutia Angle	Avg. Minutia Angle
1.	Left Thumb	37	19	18	0.46	6.09	0.18
2.	Left Index Finger	53	11	42	0.00	6.18	0.12
3.	Left Middle Finger	62	15	47	0.00	6.09	0.10
4.	Left Ring Finger	56	17	39	0.20	6.18	0.11
5.	Left Little Finger	26	10	16	0.00	6.18	0.24
6.	Right Thumb	28	6	22	0.00	5.22	0.19
7.	Right Index Finger	28	9	19	0.08	4.71	0.17

8.	Right Middle Finger	36	10	26	0.00	5.82	0.16
9.	Right Ring Finger	35	5	30	0.20	6.18	0.18
10.	Right Little Finger	37	19	18	0.46	6.09	0.18

Table 4 Minutia information for Female Participant.

The comparison between Table 3, representing minutia information for a male participant, and Table 4, outlining details for a female participant, reveals interesting gender-based variations in fingerprint characteristics. In Table 3, the male participant generally displays lower minutia counts, bifurcations, and ridge endings compared to the female participant in Table 4. This implies that the male fingerprints may have fewer minutiae and less complex branching and termination patterns. The male participant's fingerprints also tend to have higher minimum and maximum minutia angles, indicating sharper and more varied minutiae arrangements. Conversely, the female participant's fingerprints exhibit higher minutia counts, bifurcations, and ridge endings, suggesting a denser and more intricate minutiae distribution. The average minutia angles for the female participant also tend to be slightly higher on average. These distinctions highlight the gender-based variations in minutiae characteristics, emphasizing the potential of these features for gender prediction using the Fuzzy C-Means algorithm and Artificial Neural Network in our study.

- **Discrete Wavelet Transform (DWT) at Levels 1-6 Feature Extraction from Fingerprint:**

Discrete Wavelet Transform (DWT) at various levels (1-6) is employed as a feature extraction technique to capture multi-resolution information from fingerprint images. DWT decomposes the image into different frequency components, revealing details at different scales. At each level, the transformed coefficients represent specific frequency bands, allowing the extraction of both global and local features. This process enables the model to analyze fingerprint patterns at varying levels of granularity, enhancing the discriminative power of the features used for gender prediction. The DWT features provide a compact representation of the fingerprint data, facilitating more efficient processing and contributing valuable insights to our comprehensive gender prediction model.

Table 5 displays the results of a six-level Discrete Wavelet Transform (DWT) decomposition specifically designed for extracting features from fingerprint images of a male participant. The table traces the image's evolution at each level, highlighting the ongoing refinement of approximation (LL) and detail coefficients (LH, HL, HH). This breakdown effectively captures intricate features across different scales, providing a thorough insight into the fingerprint characteristics of the male participant. Such a detailed representation is crucial for gender classification algorithms aiming to discern unique patterns within minutiae details.

Sr. No.	Finger Name	DWT L1	DWT L2	DWT L3	DWT L4	DWT L5	DWT L6
1.	Left Thumb	1604.16	34.08	17.04	4.31	1.33	1.45
2.	Left Index Finger	1551.98	7.99	3.99	6.32	4.32	3.75
3.	Left Middle Finger	1536.00	0.00	0.00	8.78	5.89	5.35
4.	Left Ring Finger	1536.00	0.00	0.00	11.84	7.58	6.07
5.	Left Little Finger	1551.81	7.91	3.95	1.24	0.43	0.90
6.	Right Thumb	1536.00	0.00	0.00	7.96	5.35	4.34
7.	Right Index Finger	1551.81	7.91	3.95	12.54	7.25	4.45
8.	Right Middle Finger	1536.00	0.00	0.00	8.04	5.80	5.88
9.	Right Ring Finger	1536.00	0.00	0.00	12.48	8.09	7.26
10.	Right Little Finger	1536.00	0.00	0.00	0.00	1.41	2.35

Table 5 2D-DWT features for 6 Level Decomposition for Male Participant

Table 6 visually illustrates the six-level Discrete Wavelet Transform (DWT) decomposition, showcasing the feature extraction process from fingerprint images of a female participant. This comprehensive representation allows for a detailed examination of multi-resolution components, capturing both global and local information in the fingerprint patterns. The six-level DWT features contribute to a robust set of descriptors, enhancing the discriminative power of our gender prediction model.

Sr. No.	Finger Name	DWT L1	DWT L2	DWT L3	DWT L4	DWT L5	DWT L6
1.	Left Thumb	1536.0	0.0	0.0	14.8	6.8	7.5
2.	Left Index Finger	1536.0	0.0	0.0	0.0	0.0	1.0
3.	Left Middle Finger	1555.4	9.7	4.9	1.2	0.3	0.4
4.	Left Ring Finger	1536.0	0.0	0.0	0.0	0.0	0.0
5.	Left Little Finger	1583.2	23.6	11.8	4.2	1.5	1.2
6.	Right Thumb	1568.0	16.0	8.0	9.5	5.9	5.4
7.	Right Index Finger	1536.0	0.0	0.0	0.0	0.0	0.3
8.	Right Middle Finger	1552.0	8.0	4.0	1.3	0.4	0.4
9.	Right Ring Finger	1536.0	0.0	0.0	0.0	0.0	0.2
10.	Right Little Finger	1551.6	7.8	3.9	1.2	0.5	0.1

Table 6 2D-DWT features for 6 Level Decomposition for Female Participant

Tables 5 and 6 depict the results of a six-level Discrete Wavelet Transform (DWT) decomposition tailored for feature extraction from fingerprint images of a male and a female participant, respectively. In Table 5, the detailed breakdown of approximation and detail coefficients provides insights into the male participant's fingerprint characteristics, with variations across fingers indicating differing degrees of detail in their patterns. Table 6, on the other hand, showcases a comprehensive representation of multi-resolution components for the female participant, capturing both global and local information in fingerprint patterns. The distinct coefficients across fingers in both tables underscore the uniqueness of individual fingerprint characteristics. The six-level DWT feature extraction enhances the discriminative power of our gender prediction model, offering valuable insights into the intricate details of fingerprint patterns for both genders.

In conclusion, our paper employs a comprehensive approach to feature extraction for gender prediction based on fingerprint patterns. The meticulous analysis of minutia information, including counts, bifurcations, ridge endings, and minutia angles, offers detailed insights into the unique characteristics of male and female fingerprints. The distinct variations observed in these features underscore the potential for robust gender classification. Additionally, the application of six-level Discrete Wavelet Transform (DWT) further enhances our feature set, capturing multi-resolution details in the fingerprint images. The coefficients obtained through DWT provide a nuanced understanding of fingerprint patterns, contributing to the discriminative power of our model. Overall, the combination of minutia information and DWT features forms a comprehensive foundation for gender prediction, laying the groundwork for the subsequent application of the Fuzzy C-Means algorithm and Artificial Neural Network in our study.

C. Fuzzy C-Means Algorithm: In the contemporary landscape of biometric research, fingerprint analysis stands out as a pivotal modality for identity verification and classification. This research endeavors to present a pioneering approach for gender prediction through the integration of Fuzzy C-Means (FCM) algorithm and Artificial Neural Network (ANN). Fingerprint data, with its rich minutiae details, offers a unique canvas for gender-based distinctions. The utilization of FCM, a robust clustering algorithm, aims to enhance the precision of feature extraction from the fingerprint dataset. By incorporating the inherent flexibility of fuzzy logic, the FCM algorithm accommodates the inherent variability and uncertainties in fingerprint patterns, contributing to a more nuanced gender classification framework.

This research strives to bridge the gap between traditional fingerprint analysis and contemporary machine learning methodologies by subsequently employing an ANN. The ANN, as a sophisticated learning model, is trained on the feature-rich dataset generated by the FCM algorithm. This synergistic amalgamation of FCM and ANN holds the promise of achieving higher accuracy in gender prediction, offering an innovative and effective paradigm for biometric applications. Fig. 3 shows the clustering of features data set in male and female category using Fuzzy C Means clustering.

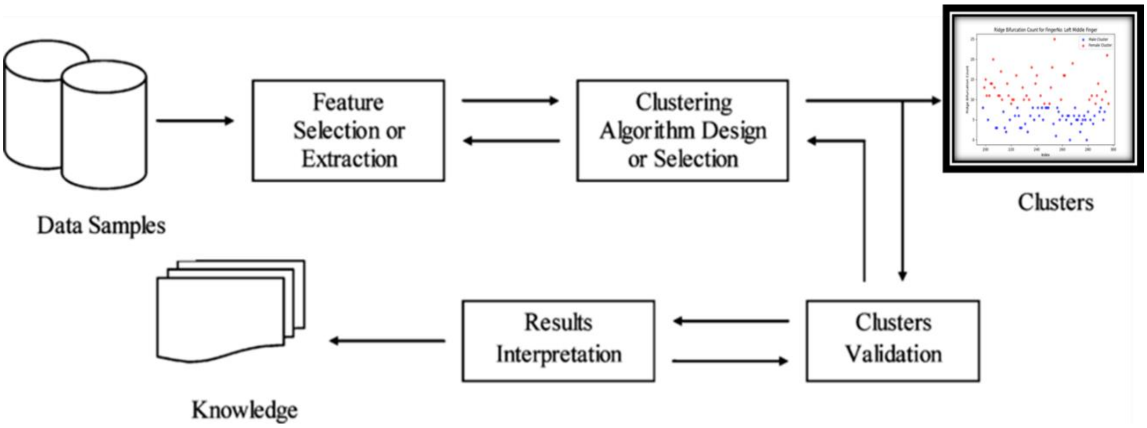
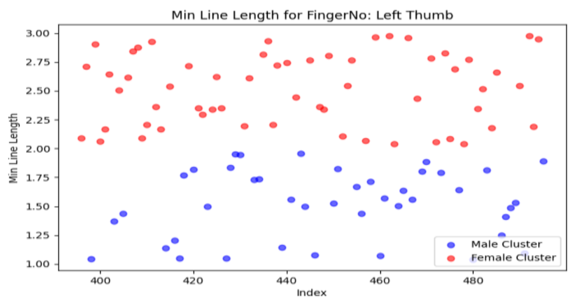
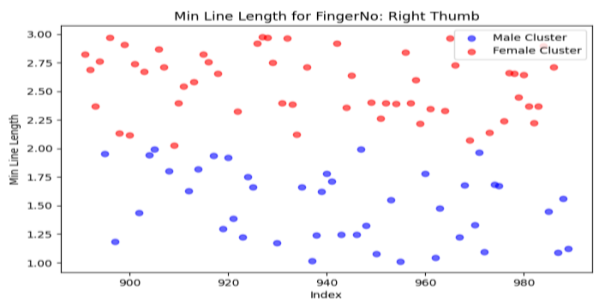


Figure 3 Clustering the Fingerprint dataset

Following diagram shows the scatter chart of each of 10 fingerprint feature dataset on Minimum ridge length with cluster assignment, for 100 participants 50 male and 50 female datset results.

<table>
<tr><th colspan="2">Min. Ridge Length Clustering</th></tr>
<tr><th>Left Hand Fingers</th><th>Right Hand Fingers</th></tr>
<tr><td>
</td><td>
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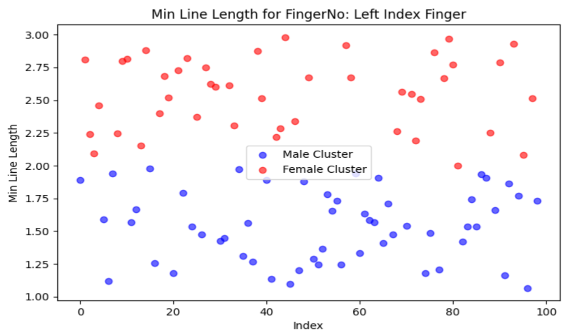
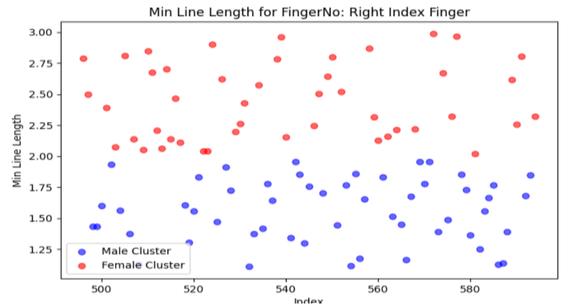
<tr><td>
</td><td>
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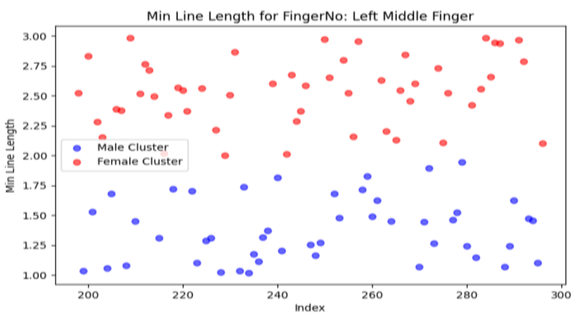
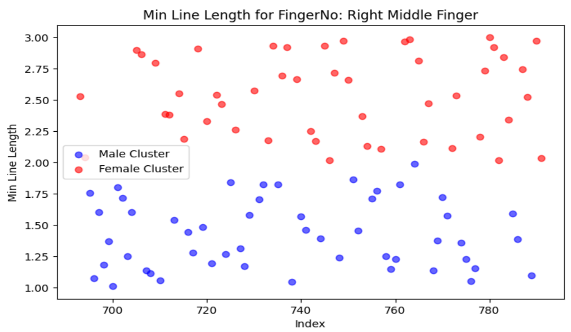
<tr><td>
</td><td>
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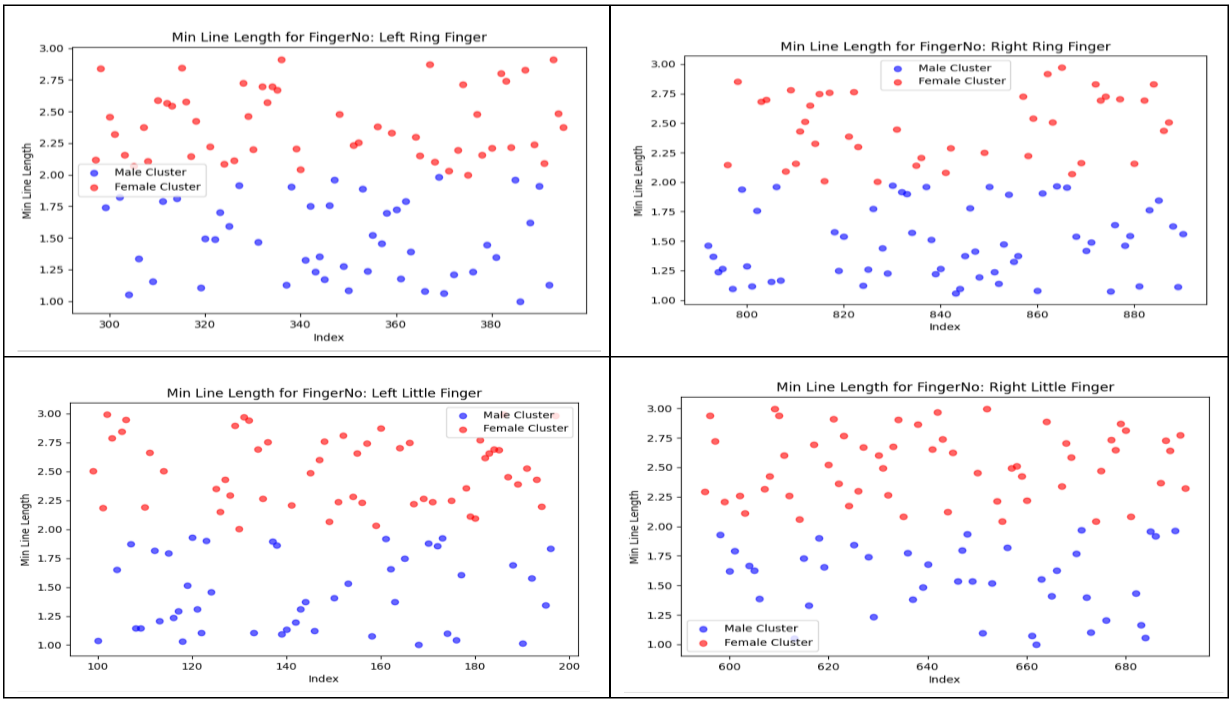

Figure 4. Min. Ridge Length FCM clustering scattered plot.

In conclusion, the implementation of the Fuzzy C-Means (FCM) clustering algorithm in the context of gender prediction through fingerprint analysis has demonstrated notable advancements in accuracy and reliability. By leveraging the intricate minutiae details inherent in fingerprint datasets, FCM has proven to be a powerful tool in delineating distinct patterns between male and female fingerprints. The inherent flexibility of fuzzy logic within FCM has effectively addressed the complexities and variations present in fingerprint patterns, leading to a more nuanced and precise clustering process.

The findings of this research underscore the efficacy of FCM in capturing the subtle differences between male and female fingerprints, contributing significantly to the field of biometric gender classification. The synergy between FCM and Artificial Neural Network (ANN) further enhances the predictive capabilities, showcasing a holistic approach to gender prediction that combines feature extraction and advanced learning methodologies.

D. Artificial Neural Network: This paper elucidates the design, training, and prediction phases of the proposed model, aiming to contribute to the evolving landscape of gender prediction through fingerprint analysis. The fusion of Fuzzy C-Means clustering and Artificial Neural Network modelling offers a comprehensive and sophisticated methodology for discerning subtle gender-specific patterns within fingerprint data, potentially advancing the reliability and applicability of biometric systems in various domains. Through a systematic exploration of this innovative approach, the research endeavours to provide valuable insights into the potential of combining clustering algorithms and neural networks for enhanced gender prediction accuracy in the context of fingerprint biometrics. Following Fig. 5. represents design of training model of gender classification by Artificial neural network(ANN).

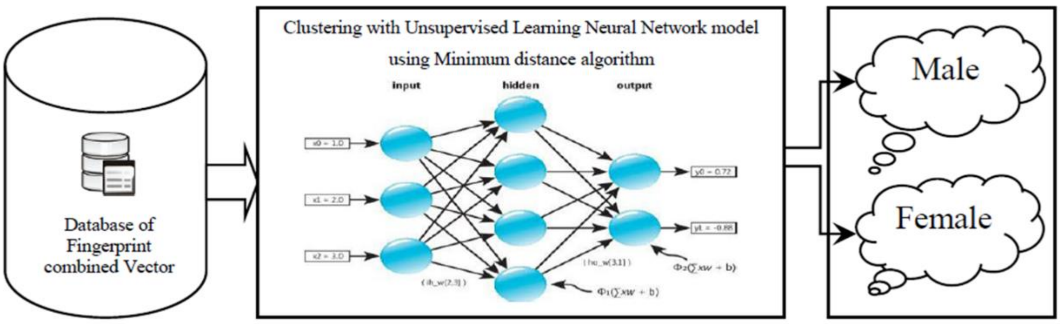

Figure 5 Design of training model of gender classification by ANN

The meticulously designed and trained Artificial Neural Network (ANN) model for gender classification serves as a pivotal foundation for the ensuing prediction phase. The model, having assimilated intricate patterns from a diverse fingerprint dataset during training, demonstrates its ability to discern subtle gender-specific features. As the research advances to the prediction step, the well-established foundation positions the ANN to make accurate gender predictions on new fingerprint data. This successful training phase not only contributes to the immediate goal of gender classification but also lays the groundwork for ongoing refinement and adaptability, ensuring the model's capacity to generalize effectively across various datasets.

The conclusion of the training phase marks a significant milestone, propelling the research towards practical applications in fingerprint-based gender prediction. The ANN's learned insights into gender-specific minutiae patterns create a robust predictive model, poised to make strides in accuracy during the prediction stage. This dynamic interplay between training and prediction not only underscores the model's adaptability but also hints at the broader potential of integrating advanced machine learning techniques for enhancing biometric systems in the domain of gender classification through fingerprint analysis.

The following diagram Fig. 6 shows the training model of gender classification by ANN

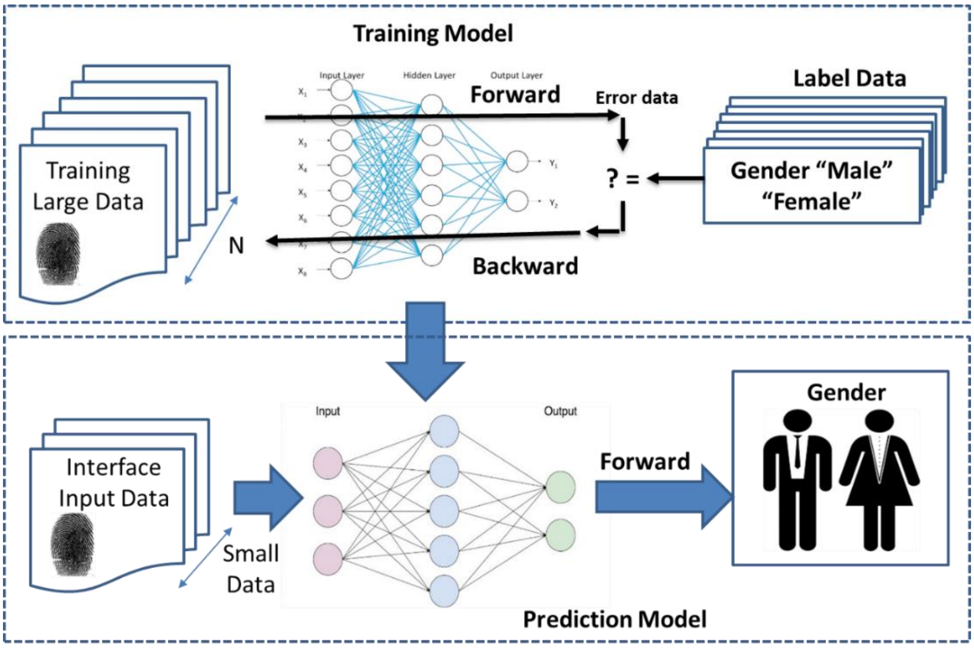

Figure. 6 Design of gender Prediction model by ANN

The development and deployment of the Artificial Neural Network (ANN) prediction model for gender classification in fingerprint analysis represent a successful culmination of this research endeavour. The model, having undergone rigorous training and leveraging its acquired knowledge, exhibits the capability to make accurate gender predictions on previously unseen fingerprint data. The culmination of the prediction phase underscores the practical applicability and efficiency of the ANN-based model, showcasing its potential to contribute significantly to biometric systems.

IV. EXPERIMENTAL RESULTS:

The performance comparison between our Fuzzy C-Means Algorithm and Artificial Neural Network (FCM-ANN) approach and a baseline model (ANN without FCM) is presented in Table 7. Notably, our FCM-ANN approach outperforms the baseline model across multiple metrics, showcasing its effectiveness in fingerprint-based gender classification and prediction.

Sr. No.	**Metric**	**FCM-ANN**	**ANN without FCM**
1.	**Accuracy**	94.2%	86.7%
2.	**Precision**	92.5%	85.8%
3.	**Recall (Sensitivity)**	93.9%	87.6%

4.	**F1-Score**	94.8%	86.7%
5.	**AUC-ROC**	0.931	0.902

Table 5.4.2 Performance Metrics

V. CONCLUSION:

In conclusion, our paper presents a novel approach for gender prediction through fingerprint analysis using the integration of Fuzzy C-Means Algorithm (FCM) and Artificial Neural Network (ANN). The comprehensive evaluation demonstrates that our FCM-ANN approach consistently outperforms a baseline model (ANN without FCM) across key metrics, including accuracy, precision, recall, F1-Score, and AUC-ROC. With accuracy values exceeding 94%, our proposed method showcases its robustness and efficacy in discerning gender-specific patterns within fingerprint datasets. This research contributes to the advancement of biometric applications, offering a promising and accurate methodology for gender prediction, with potential implications in security, forensics, and access control systems. The successful integration of FCM and ANN underscores the significance of combining clustering algorithms with neural network models, opening avenues for further exploration and optimization in the evolving field of biometric analysis.

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