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Hypergraph Neural Networks for Robust Fingerprint Matching in Forensic Applications

Assistant Professor Dr. Pankaj Malik, Lakshita Singh, Yashi Sethi, Dixika Verma, Dev Soni
Computer Science Engineering
Medi-Caps University, Indore, India

Abstract- Fingerprint matching is a crucial task in forensic science, where the accurate and reliable identification of individuals is essential for criminal investigations. Traditional fingerprint matching algorithms often struggle with challenges such as occlusion, distortion, and partial prints. In this study, we propose a novel approach that leverages Hypergraph Neural Networks (HGNNs) to enhance the robustness and accuracy of fingerprint matching in forensic applications. By modeling fingerprint features as hypergraphs, we capture higher-order relationships between minutiae points and their spatial configurations, enabling more effective matching despite partial or degraded fingerprints. The HGNN framework integrates both local and global feature information, improving the system's ability to recognize subtle and complex patterns in fingerprint data. Extensive experiments on benchmark fingerprint datasets demonstrate that our approach outperforms conventional methods in terms of matching accuracy and robustness to noise. The proposed HGNN-based model provides a promising solution for advancing forensic fingerprint identification systems, offering improved performance under challenging real-world conditions.

Index Terms- Hypergraph Neural Networks (HGNN), Fingerprint Matching, Forensic Applications, Robust Identification, Minutiae Extraction, Partial Fingerprints, Pattern Recognition, Forensic Science, Graph-Based Models, Biometrics, Fingerprint Recognition Systems.

I. INTRODUCTION

Fingerprint identification has long been a cornerstone of forensic science, serving as one of the most reliable biometric traits for criminal investigations, personal identification, and security systems. Over the years, various automated fingerprint identification systems (AFIS) have been developed to enhance the accuracy and efficiency of fingerprint matching. However, traditional fingerprint matching methods often face significant challenges when dealing with partial prints, noise, distortion, or occlusion, which are commonly encountered in real-world forensic scenarios. These limitations hinder the reliability and robustness of existing fingerprint recognition systems.

Recent advancements in deep learning have revolutionized many areas of pattern recognition, yet conventional neural network architectures may not fully address the inherent complexities of fingerprint matching. Traditional approaches primarily focus on local feature matching, such as minutiae points, without capturing the intricate relationships between them. As a result, they may struggle to generalize in the presence of distorted or incomplete fingerprints.

To overcome these challenges, this paper proposes the use of Hypergraph Neural Networks (HGNNs), an advanced graph-based learning technique, to improve the robustness and accuracy of fingerprint matching in forensic applications. Hypergraphs, which generalize traditional graphs by allowing edges to connect multiple nodes simultaneously, offer a more comprehensive representation of fingerprint features. By modeling minutiae points and their spatial relationships as a hypergraph, the proposed method can better capture complex patterns and higher-order dependencies among the features.

In this study, we explore the potential of HGNNs to address the limitations of conventional fingerprint matching techniques. We present a framework that integrates both local and global fingerprint information, enhancing the system's ability to recognize and match partial or degraded prints. The proposed model is evaluated on multiple benchmark fingerprint datasets, demonstrating its superior performance compared to existing methods in terms of accuracy and robustness.

The rest of this paper is organized as follows: Section 2 reviews related work in fingerprint matching and deep learning techniques. Section 3 presents the methodology and architecture of the HGNN-based fingerprint matching model.

Section 4 details the experimental setup, datasets, and results. Finally, Section 5 concludes the study and discusses potential future directions for research.

II. LITERATURE REVIEW

Fingerprint matching has been a critical area of research in forensic science, with a substantial body of work focusing on improving accuracy, speed, and robustness. This section provides an overview of existing techniques and recent advancements in fingerprint recognition, highlighting the role of deep learning, graph-based models, and the potential application of Hypergraph Neural Networks (HGNNs).

1. Traditional Fingerprint Matching Techniques
Historically, fingerprint recognition methods have been based on classical image processing and feature-based approaches, such as minutiae-based matching. Minutiae points, which include ridge endings, bifurcations, and other distinctive features, are commonly extracted from fingerprints and used for matching. Early systems relied heavily on geometric matching algorithms that compared minutiae patterns based on their spatial relationships. However, these methods often struggled in scenarios with partial prints, distortion, or noise. Furthermore, computational inefficiency and the inability to capture non-linear dependencies in the feature space limited the performance of these traditional systems.

2. Deep Learning in Fingerprint Recognition
In recent years, deep learning techniques have been applied to enhance fingerprint recognition, particularly in handling large and complex datasets. Convolutional Neural Networks (CNNs) have been the predominant architecture due to their ability to extract hierarchical features from images. Several studies have shown the effectiveness of CNNs in fingerprint classification, feature extraction, and matching tasks, providing robustness against challenges like rotation and scale variations. Despite their success, CNN-based methods primarily focus on local features, which limits their ability to capture global contextual information and higher-order relationships among minutiae points.

3. Graph-Based Models for Fingerprint Matching
Graph-based approaches have gained attention in various biometric systems due to their ability to model the relationships between features in a structured and flexible manner. Fingerprints can be naturally represented as graphs, where minutiae points serve as nodes and the spatial relationships between them are captured as edges. Techniques such as Graph Neural Networks (GNNs) have been applied to fingerprint recognition with promising results. GNNs can learn spatial dependencies between features and improve matching accuracy by integrating global information. However, traditional GNNs are limited by their reliance on pairwise relationships between features, which may not fully capture the complexities of the fingerprint's structure.

4. Hypergraph Neural Networks (HGNNs) for Pattern Recognition
Hypergraph Neural Networks (HGNNs) are an extension of GNNs that model relationships among more than two nodes simultaneously, offering a more generalized approach for graph-based learning. In the context of fingerprint matching, this means that the model can capture higher-order interactions between minutiae points, rather than merely considering pairwise connections. HGNNs have been successfully applied in various domains, including social networks, recommendation systems, and computer vision, where higher-order dependencies are crucial. These networks are particularly beneficial for modeling complex data structures like fingerprints, where relationships between features are non-trivial and involve multiple interactions.

Recent research has demonstrated the potential of HGNNs in tasks that require the analysis of complex, structured data. For instance, a study by [Author et al., 2020] introduced HGNNs for multi-label classification in image recognition, showing significant improvements over traditional graph-based models. Similarly, [Author et al., 2021] applied HGNNs to human pose estimation, where higher-order relationships between body parts were crucial for accurate predictions. These results suggest that HGNNs could provide a promising approach for addressing the challenges faced in fingerprint matching, particularly in the presence of partial, noisy, or distorted prints.

5. Challenges in Forensic Fingerprint Matching
Fingerprint recognition in forensic applications often involves matching degraded, incomplete, or distorted prints, which poses significant challenges for traditional and deep learning-based methods. Existing systems may struggle with issues such as:

- **Partial Prints:** Incomplete or fragmented prints are common in forensic investigations, especially when dealing with prints left on irregular surfaces.
- **Noise and Distortion:** Environmental factors, aging of prints, or poor-quality imaging can distort fingerprint features.
- **Scalability and Efficiency:** With the growing number of fingerprints stored in databases, achieving real-time performance and scalability becomes increasingly important.

While some advancements have been made to address these challenges, most approaches still rely on local feature matching or do not fully integrate the complex spatial relationships among minutiae points. The adoption of HGNNs in fingerprint matching offers a novel approach to capture these higher-order relationships, potentially enhancing the robustness and accuracy of the recognition process.

Research Gap
Despite significant progress in the field of fingerprint recognition, several challenges remain that hinder the effectiveness and reliability of existing systems, particularly in forensic applications. A thorough examination of the literature reveals the following key gaps that this research aims to address:

Limited Robustness to Partial and Degraded Fingerprints
Traditional fingerprint matching techniques, including minutiae-based and image-based methods, struggle to match partial or degraded prints. While deep learning models, especially Convolutional Neural Networks (CNNs), have been shown to improve matching accuracy, they often fail to effectively handle distorted or noisy fingerprints. Many deep learning models rely on local feature matching and may overlook the complex spatial relationships between features, resulting in decreased performance when dealing with incomplete prints. There is a need for more robust systems that can match partial and degraded fingerprints with high accuracy.

Inability to Model Higher-Order Relationships
Most existing graph-based fingerprint matching methods, including Graph Neural Networks (GNNs), focus on pairwise relationships between fingerprint features, such as minutiae points. However, these methods may not fully capture the higher-order dependencies among minutiae, which are critical for accurate matching, especially when fingerprints are incomplete or distorted. Existing approaches overlook the possibility of incorporating richer, higher-dimensional feature interactions, which can better represent the complex structure of fingerprints. Hypergraph Neural Networks (HGNNs) offer a promising solution by modeling multi-way interactions, which has not been sufficiently explored in the context of fingerprint recognition.

Lack of Comprehensive Evaluation on Forensic Datasets
While many fingerprint recognition methods have been evaluated on benchmark datasets, there is a lack of comprehensive evaluations using real-world forensic fingerprint data, which often includes partial, noisy, or low-resolution prints. Most studies use controlled, clean datasets where the prints are ideal, which does not reflect the true challenges faced in forensic investigations. To truly assess the robustness of fingerprint matching algorithms in practical scenarios, it is crucial to test these models on datasets that closely resemble real-world forensic conditions.

Challenges with Scalability and Real-Time Performance
Fingerprint identification systems, particularly those used in large-scale forensic databases, require scalability and real-time processing capabilities. While recent advances in deep learning have shown promise, there is still a gap in developing models that balance high accuracy with computational efficiency. The growing volume of fingerprints stored in databases requires algorithms that can scale without sacrificing performance. Furthermore, real-time processing remains a challenge when dealing with complex, graph-based models like GNNs and HGNNs. Thus, research is needed to optimize these models for faster inference times while maintaining their accuracy and robustness.

Lack of Integration of Multi-Modal Data
Many fingerprint matching techniques focus solely on fingerprint images without considering other potentially valuable sources of information, such as demographic data, environmental factors, or contextual information. The integration of multi-modal data can enhance the performance of fingerprint matching systems, especially in challenging forensic cases where prints may be ambiguous or incomplete. There is a gap in research that explores how multi-modal data, in combination with graph-based techniques, could improve the robustness and accuracy of fingerprint recognition.

III. METHODOLOGY

This section outlines the methodology employed in this research to enhance the robustness and accuracy of fingerprint matching using Hypergraph Neural Networks (HGNNs). The methodology consists of three main phases: data preparation, hypergraph network design, and model training and evaluation. Each phase is designed to address the challenges identified in the research gap, including partial and degraded prints, the modeling of higher-order relationships among minutiae, and scalability.

1. Data Collection and Preprocessing
To evaluate the proposed HGNN-based approach, we utilized a combination of publicly available benchmark fingerprint datasets and real-world forensic datasets. The datasets consist of both high-quality and degraded fingerprint images, providing a comprehensive range of fingerprint conditions encountered in forensic investigations.

- **Benchmark Datasets:** We used standard datasets such as the FVC (Fingerprint Verification Competition) and NIST Special Database 4, which provide a wide variety of fingerprint images with varying quality and resolution.
- **Forensic Datasets:** In addition to benchmark datasets, real-world forensic fingerprint data were collected from collaborating forensic institutions, including partial, noisy, and distorted prints.

Preprocessing Steps
- **Fingerprint Enhancement:** We applied image enhancement techniques such as ridge flow correction,

contrast enhancement, and noise reduction to improve the quality of degraded fingerprints.

- **Minutiae Extraction:** A minutiae extraction algorithm was employed to detect ridge endings, bifurcations, and other critical features. These minutiae points form the nodes of the hypergraph.
- **Fingerprint Normalization:** Fingerprint images were normalized to standard sizes and orientations to ensure consistency in feature extraction and comparison.

2. Hypergraph Construction

The key innovation of this methodology lies in modeling the fingerprint as a hypergraph, where minutiae points are treated as nodes, and the relationships between them are captured through hyperedges. Hyperedges connect multiple nodes, allowing the model to learn higher-order dependencies among minutiae points.

- **Minutiae Representation:** Each minutiae point is represented by its spatial coordinates (x, y), ridge direction, and type (ending or bifurcation). These attributes are used as node features in the hypergraph.
- **Hyperedge Construction:** Hyperedges are constructed by considering spatial proximity and angular relationships between minutiae points. For example, minutiae points within a predefined radius and angular range are grouped together in a hyperedge. Additionally, the connectivity of minutiae points is adjusted based on local and global structures of the fingerprint, such as the overall ridge pattern and minutiae density.

Hypergraph Design

- **Global Connectivity:** A set of hyperedges is designed to connect nodes that share higher-order spatial relationships, taking into account the overall ridge structure of the fingerprint.
- **Local Connectivity:** Hyperedges are also formed between minutiae points that are spatially close, providing a local context for matching.
- **Edge Weights:** Weights are assigned to hyperedges based on the proximity, angle, and similarity of minutiae points. This weighting mechanism helps prioritize more reliable features during the matching process.

3. Hypergraph Neural Network Architecture

The HGNN architecture is designed to learn both local and global dependencies among minutiae points, enhancing the model's ability to recognize complex fingerprint patterns.

- **Input Layer:** The input to the HGNN is a hypergraph representation of the fingerprint, where each node corresponds to a minutiae point, and hyperedges encode the higher-order relationships.
- **Graph Convolution Layer:** A Hypergraph Convolutional Network (HCN) layer is employed to update node features by aggregating information from neighboring nodes connected via hyperedges. This allows the model to learn contextual information from both local and global spatial relationships between minutiae.
- **Attention Mechanism:** An attention mechanism is integrated into the HGNN to dynamically adjust the importance of each minutiae point and its associated hyperedge during the feature aggregation process. This helps the model focus on more reliable and informative features, especially in the case of partial or noisy fingerprints.
- **Fully Connected Layers:** After the graph convolutional layers, the output is passed through fully connected layers that map the learned features into a matching score.
- **Output Layer:** The output of the network is a similarity score between the query fingerprint and the stored fingerprint in the database. A higher score indicates a closer match.

4. Model Training

The HGNN model is trained using a supervised learning approach, where the goal is to minimize the matching error between the query fingerprint and the correct match. The following steps are followed during training:

- **Loss Function:** A contrastive loss function is used to minimize the difference between correct matches and false matches. The loss function encourages the model to output high similarity scores for true matches and low scores for non-matches.
- **Optimization:** The model is optimized using the Adam optimizer, with early stopping to prevent overfitting. We apply a learning rate scheduler to gradually decrease the learning rate during training.
- **Regularization:** Dropout and L2 regularization are applied to prevent overfitting and ensure the model generalizes well to unseen fingerprint data.

5. Model Evaluation

The performance of the HGNN-based fingerprint matching system is evaluated using the following metrics:

- **Matching Accuracy:** The percentage of correctly matched fingerprints out of all tested pairs.
- **False Match Rate (FMR) and False Non-Match Rate (FNMR):** These rates are computed to evaluate the reliability and robustness of the system, especially in challenging scenarios involving partial or noisy fingerprints.
- Precision, Recall, and F1-Score: These metrics are used to assess the trade-off between precision and recall, providing a comprehensive evaluation of model performance.
- **Computational Efficiency:** In addition to accuracy, the time taken for fingerprint matching (inference time) is measured to assess the model’s scalability and suitability for real-time applications.

6. Comparison with Existing Methods
To validate the effectiveness of the proposed HGNN-based approach, the results are compared with traditional fingerprint matching algorithms (e.g., minutiae-based matching, CNN-based models) and other graph-based methods (e.g., GNNs). Performance comparisons are conducted using both benchmark and real-world forensic datasets, focusing on matching accuracy, robustness to noise, and computational efficiency.

IV. EXPERIMENTAL SETUP

This section describes the experimental setup used to evaluate the performance of the Hypergraph Neural Network (HGNN) model for robust fingerprint matching. The experimental process involves model configuration, training procedures, and evaluation protocols to ensure comprehensive testing under different conditions, including high-quality, partial, noisy, and distorted fingerprints.

1. Hardware Configuration
The experiments were conducted on a high-performance computing system equipped with the following specifications:
- Processor: Intel Core i9-10900K (10 cores, 3.7 GHz base clock)
- Graphics Card: NVIDIA GeForce RTX 3090 with 24 GB of GDDR6X VRAM
- RAM: 64 GB DDR4 RAM
- Storage: 2 TB SSD for fast data loading and storage
- Operating System: Ubuntu 20.04 LTS
- Software Environment: Python 3.8, TensorFlow 2.7, PyTorch 1.10, and CUDA 11.2

This hardware setup ensured that the computational demands of training the HGNN model, including handling large datasets and performing graph convolutions, were met efficiently.

2. Model Configuration
The Hypergraph Neural Network (HGNN) model was implemented using the PyTorch framework with the following configuration:

Node Features: Each minutiae point is represented by a 4-dimensional feature vector consisting of:
- Spatial coordinates (x, y) normalized to the range [0, 1].
- Ridge direction (theta) encoded as a 2D vector using polar coordinates.
- Minutiae type (ending or bifurcation) encoded as a one-hot vector.

Hypergraph Construction
- **Proximity-Based Hyperedges:** Minutiae points within a radius of 10 pixels were connected to form hyperedges. The distance threshold was adjusted based on the dataset's resolution.
- **Angle-Based Hyperedges:** Minutiae points with similar ridge orientations (within a 30° angular range) were grouped into the same hyperedge.
- **Global and Local Connectivity:** Local connectivity captured minute proximity relationships, while global connectivity considered the overall ridge structure to enhance matching accuracy.

Graph Convolutional Layer
- **Hypergraph Convolution Layer (HCN):** The aggregation function in the graph convolution layer was designed to capture multi-way interactions by considering the higher-order relationships of minutiae points within hyperedges.
- **Attention Mechanism:** A self-attention mechanism was integrated to adaptively weight the importance of nodes and edges during the feature aggregation process.

Network Architecture
- **Input Layer:** Node features (minutiae attributes) were input into the network along with the hypergraph connectivity matrix.
- **Hidden Layers:** Three graph convolutional layers were applied to propagate node features across the hypergraph. Each layer was followed by a ReLU activation function.
- **Fully Connected Layers:** Two fully connected layers after the convolutional layers, with 512 and 256 units respectively, were used to map the learned features to the matching score.
- **Output Layer:** A sigmoid activation function was used to produce a similarity score between 0 and 1, indicating how closely a query fingerprint matches a stored fingerprint.

3. Training Procedure
The HGNN model was trained using a supervised learning approach with the following training protocol:
- **Batch Size:** A batch size of 32 was used during training to balance computational efficiency and model performance.
- **Learning Rate:** An initial learning rate of 0.001 was used, which was reduced by a factor of 0.1 after every 5 epochs if the validation loss plateaued.
- **Optimizer:** The Adam optimizer with a weight decay of 0.0001 was used to minimize the loss function.
- **Loss Function:** A contrastive loss function was employed to optimize the matching score. The loss function encourages the model to output high similarity scores for true matches and low scores for false matches.
- **Epochs:** The model was trained for a total of 50 epochs, with early stopping implemented if the validation accuracy did not improve after 10 consecutive epochs.

4. Evaluation Protocol

The evaluation of the HGNN model was conducted on both benchmark and forensic datasets to test its robustness under different fingerprint conditions. The following evaluation protocols were followed:

Performance Metrics: The following metrics were used to evaluate the model's effectiveness:

- **Matching Accuracy:** The percentage of correctly matched fingerprint pairs.
- **False Match Rate (FMR):** The rate of incorrect matches (false positives).
- **False Non-Match Rate (FNMR):** The rate of failure to identify true matches (false negatives).
- **Precision, Recall, and F1-Score:** These metrics were calculated to assess the trade-off between precision and recall, providing a comprehensive evaluation of the model's ability to identify true matches while minimizing errors.
- **Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC):** Used to evaluate the overall classification performance across various thresholds.

Comparison with Baselines: The HGNN-based model was compared with several baseline fingerprint matching algorithms:

- **Minutiae-Based Matching:** A traditional method based on spatial matching of minutiae points.
- **Convolutional Neural Networks (CNNs):** A CNN-based model trained to classify fingerprint images.
- **Graph Neural Networks (GNNs):** A graph-based model using pairwise relationships between minutiae points.

Testing Conditions: The model was tested under various conditions, including:

- **High-Quality Fingerprints:** Full, high-resolution fingerprint images with clear minutiae points.
- **Partial Fingerprints:** Incomplete fingerprints with missing or fragmented minutiae.
- **Noisy Fingerprints:** Prints affected by environmental noise, smudges, or low-resolution sensors.
- **Distorted Fingerprints:** Prints affected by surface irregularities or skin deformation.

5. Computational Efficiency

To assess the scalability of the proposed model, the inference time for matching a query fingerprint with a database of 10,000 prints was measured.

Additionally, the memory usage and computational cost were evaluated to ensure the model can operate efficiently in real-time forensic applications.

Dataset

To evaluate the performance of the proposed Hypergraph Neural Network (HGNN) model for fingerprint matching, we used a combination of publicly available benchmark datasets and real-world forensic fingerprint data. The datasets include a variety of fingerprint images, ranging from high-quality prints to partial, noisy, and degraded prints, which simulate the conditions commonly encountered in forensic investigations. The following datasets were used in this study:

1. FVC (Fingerprint Verification Competition) Datasets

The FVC datasets are widely used in fingerprint recognition research and provide a standard benchmark for evaluating fingerprint matching algorithms. We utilized multiple subsets from the FVC 2000, 2002, and 2004 competitions, which offer a range of fingerprint images under different conditions, including:

- **FVC 2000:** Contains fingerprints from 100 subjects, each with 8 samples captured under controlled conditions.
- **FVC 2002:** Comprises 400 fingerprint images from 100 individuals, with varying degrees of quality.
- **FVC 2004:** Includes a set of fingerprints from 80 subjects, with both high-quality and degraded prints.

These datasets provide well-structured, high-resolution images that are useful for training and testing the proposed HGNN model. The FVC datasets offer various image quality levels, which enable the evaluation of the model's robustness under different conditions.

NIST Special Database 4

The NIST Special Database 4 is a comprehensive collection of fingerprint images provided by the National Institute of Standards and Technology (NIST). It includes 2,000 fingerprint cards, with images from different acquisition devices and conditions. The dataset contains both rolled and plain impressions of fingerprints and is widely used for evaluating the performance of fingerprint matching systems.

- **Roll-Impression Prints:** Full fingerprint images with high-quality impressions.
- **Plain-Impression Prints:** Partial fingerprints captured on flat surfaces.

The diversity in acquisition techniques and image quality in this dataset is valuable for assessing the generalizability of the HGNN-based model to real-world forensic scenarios.

Forensic Fingerprint Dataset

In addition to benchmark datasets, we collected a real-world forensic fingerprint dataset from collaborating forensic institutions. This dataset was specifically designed to simulate the challenges faced in actual criminal investigations, including:

- **Partial Fingerprints:** Images that contain only a portion of the fingerprint, commonly encountered in crime scene investigations where fingerprints are smeared or incomplete.
- **Distorted Fingerprints:** Prints that are deformed due to surface irregularities or environmental factors (e.g., weather conditions, skin abrasions).
- **Noisy Fingerprints:** Low-resolution prints that may be affected by dirt, smudges, or poor-quality sensors.

This dataset provides a more realistic testing ground for evaluating the robustness of fingerprint matching systems in scenarios where prints may not be as clean or complete as in controlled environments.

Preprocessing and Augmentation

To enhance the diversity and robustness of the model, several preprocessing and data augmentation techniques were applied to the datasets:

- **Noise Addition:** Random noise was added to simulate fingerprint distortion due to poor image quality.
- **Rotation and Scaling:** Fingerprints were rotated and scaled to simulate variations in orientation and size, which commonly occur during real-world fingerprint capture.
- **Partial Fingerprint Simulation:** Partial fingerprints were artificially created by cropping sections of the original images to simulate missing or incomplete prints.

These augmentation techniques allow the model to better generalize and handle various fingerprint matching scenarios, especially in forensic applications.

Dataset Splitting

For training and evaluation, the datasets were divided into training, validation, and test sets:

- **Training Set:** 70% of the total dataset was used for training the HGNN model. This set contains both high-quality and degraded fingerprints to ensure the model learns to handle various conditions.
- **Validation Set:** 15% of the dataset was used for hyperparameter tuning and model selection.
- **Test Set:** 15% of the dataset was reserved for final evaluation to assess the performance of the model on unseen data.

The splitting was done in such a way that each set contained a balanced distribution of high-quality, partial, noisy, and distorted fingerprints to ensure that the evaluation metrics accurately reflect the model's performance across different fingerprint conditions.

V. RESULTS AND DISCUSSION

This section presents the results of the experiments conducted to evaluate the performance of the Hypergraph Neural Network (HGNN) model for fingerprint matching. The experimental setup, as described earlier, involved testing the model on a combination of benchmark datasets and real-world forensic datasets, with various fingerprint conditions such as high-quality, partial, noisy, and distorted prints. The model's performance is compared with several baseline methods, including minutiae-based matching, convolutional neural networks (CNNs), and graph neural networks (GNNs).

1. Performance on Benchmark Datasets

Table 1 presents the matching accuracy, false match rate (FMR), and false non-match rate (FNMR) for the HGNN model, along with the comparison to baseline methods on the FVC and NIST datasets.

Method	Dataset	Accuracy (%)	FMR (%)	FNMR (%)
HGNN	FVC 2000	97.5	0.12	1.3
HGNN	FVC 2002	96.2	0.15	2.1
HGNN	FVC 2004	95.8	0.20	1.9
Minutiae-Based Matching	FVC 2000	91.4	0.35	6.2
Minutiae-Based Matching	FVC 2002	88.9	0.45	7.5
CNN-Based Model	FVC 2000	92.0	0.30	4.1
CNN-Based Model	FVC 2002	89.6	0.35	5.6
GNN-Based Model	FVC 2000	94.7	0.25	3.7
GNN-Based Model	FVC 2002	92.1	0.30	4.4

- **HGNN Performance:** The HGNN model outperformed the traditional minutiae-based method and CNN-based models in terms of matching accuracy, FMR, and FNMR. On the FVC datasets, the HGNN achieved accuracies of 97.5%, 96.2%, and 95.8% on the FVC 2000, 2002, and 2004 datasets, respectively, which were significantly higher than the CNN and GNN models.
- **Baseline Comparisons:** While the CNN-based models performed reasonably well, their performance was still inferior to that of the HGNN, especially in handling partial and noisy fingerprints. The minutiae-based method, which relies on simple spatial matching,

struggled with more complex cases, such as distorted or incomplete prints.

2. Performance on Forensic Datasets
Table 2 summarizes the precision, recall, and F1-score of the HGNN model on real-world forensic fingerprint data, compared with baseline methods.

Method	Forensic Dataset	Precision (%)	Recall (%)	F1-Score (%)
HGNN	Forensic 1 (Partial, Noisy)	94.3	92.8	93.5
HGNN	Forensic 2 (Distorted, Noisy)	92.1	89.7	90.9
Minutiae-Based Matching	Forensic 1	84.2	78.4	81.2
Minutiae-Based Matching	Forensic 2	78.9	74.3	76.5
CNN-Based Model	Forensic 1	89.0	83.5	86.1
CNN-Based Model	Forensic 2	86.5	80.2	83.3
GNN-Based Model	Forensic 1	91.7	88.4	90.0
GNN-Based Model	Forensic 2	89.1	85.2	87.1

- **HGNN Performance on Forensic Data:** The HGNN model exhibited impressive results on the forensic datasets, achieving precision scores of 94.3% and 92.1% on the partial, noisy and distorted, noisy datasets, respectively. The model's recall and F1-scores were also higher than the baselines, indicating its superior ability to recover true matches in challenging conditions.
- **Baseline Comparisons:** The minutiae-based method struggled significantly with partial, noisy, and distorted prints, as reflected in its low precision and recall. CNN-based models performed better than minutiae-based approaches but were still unable to match the robustness of the HGNN, especially in the presence of distortion and noise. The GNN-based model performed better than the CNN but still lagged behind the HGNN in both recall and F1-score.

3. Performance on Real-World Scenarios
The inference time and memory usage of the HGNN model were also assessed to determine its suitability for real-time forensic applications. The model's inference time for matching a query fingerprint against a database of 10,000 prints was measured at 1.2 seconds, which is efficient for real-time applications. The memory usage during inference was approximately 4 GB, which is manageable for deployment on modern forensic workstations.

4. Discussion: Key Insights
- **Improved Robustness:** The HGNN model excels in robustness, especially under challenging conditions like partial, noisy, and distorted fingerprints. By utilizing the hypergraph structure, which captures higher-order relationships among minutiae points, the model significantly outperforms traditional minutiae-based matching methods and other graph-based approaches.
- **Generalization to Forensic Scenarios:** The model's ability to generalize to real-world forensic data is a key advantage. In contrast to CNNs and GNNs, which rely on local pixel-level features, the HGNN model effectively captures both local and global dependencies, making it well-suited for forensic applications where fingerprint quality varies greatly.
- **Scalability:** The HGNN model's relatively low inference time ensures that it can handle large fingerprint databases efficiently, making it suitable for large-scale forensic investigations.

5. Limitations and Future Work
While the HGNN model outperforms traditional methods, there are several areas for improvement and future work:
- **Scalability:** As the number of fingerprints in the database grows, the model's computational efficiency can be further optimized. Techniques such as approximate nearest neighbor search and graph partitioning could be explored to speed up inference times for large-scale fingerprint matching systems.
- **Data Diversity:** The model's performance could benefit from a more diverse set of forensic fingerprints, including prints from different ethnicities, age groups, and environmental conditions. Expanding the dataset to include such variations could further enhance the robustness of the system.
- **Transfer Learning:** Future work could explore the use of transfer learning to fine-tune the HGNN model on domain-specific forensic fingerprint data, reducing the need for large-scale labeled datasets.

VI. CONCLUSION

In this study, we proposed a novel Hypergraph Neural Network (HGNN) approach for robust fingerprint matching in forensic applications. The proposed model leverages the power of hypergraph structures to capture the higher-order relationships between minutiae points, enabling it to effectively handle partial, noisy, and distorted fingerprints, which are common in real-world forensic scenarios.

The experimental results demonstrated that the HGNN model outperformed traditional fingerprint matching methods, such as minutiae-based matching, and deep learning-based models like convolutional neural networks (CNNs) and graph neural networks (GNNs). On benchmark datasets, the HGNN achieved higher matching accuracy, lower false match rates (FMR), and false non-match rates (FNMR) compared to the baseline methods. Furthermore, on real-world forensic datasets with challenging conditions, including partial, noisy, and distorted prints, the HGNN model exhibited superior precision, recall, and F1-scores.

Key contributions of this work include:

- The use of hypergraph structures to model complex, higher-order relationships between minutiae points, which enhances the model's ability to process partial and noisy prints.
- The incorporation of a self-attention mechanism within the HGNN, which enables the model to focus on the most relevant minutiae features during the matching process.
- An evaluation of the model's performance on both benchmark and real-world forensic datasets, highlighting its robustness in various fingerprint conditions.

While the proposed HGNN model achieved promising results, further work is needed to optimize its scalability for large-scale fingerprint databases and to extend its application to more diverse fingerprint data. Future research could explore techniques such as approximate nearest neighbor search, graph partitioning, and transfer learning to enhance the efficiency and generalizability of the model.

In conclusion, the HGNN model represents a significant advancement in fingerprint matching technology, providing a powerful tool for forensic applications. Its robustness to challenging fingerprint conditions makes it particularly suitable for criminal investigations, biometric authentication, and security applications where fingerprint quality is often suboptimal.

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