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Image-Based Missing Child Reclamation Model Using Deep Learning

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***Abstract*--The growing number of missing children cases in India necessitates advanced technological interventions for efficient identification and recovery. This research presents a deep learning-based system that automates the process of missing child identification using facial recognition. The proposed approach integrates Multi-task Cascaded Convolutional Networks (MTCNN) for face detection and alignment, and InceptionResNetV1 for feature extraction, ensuring robust and accurate identification. Additionally, an age estimation module is incorporated to account for facial changes over time, improving the system's effectiveness in long-term missing cases. By leveraging deep learning techniques and real-time image matching, the system achieves a high accuracy of 99.4%, significantly surpassing traditional search methods. Furthermore, the integration of public image uploads and law enforcement databases enhances scalability, making it suitable for large-scale implementations. This AI-driven framework offers a reliable, real-time, and automated solution to improve the efficiency of missing child identification, ultimately aiding in faster and more successful recoveries.**

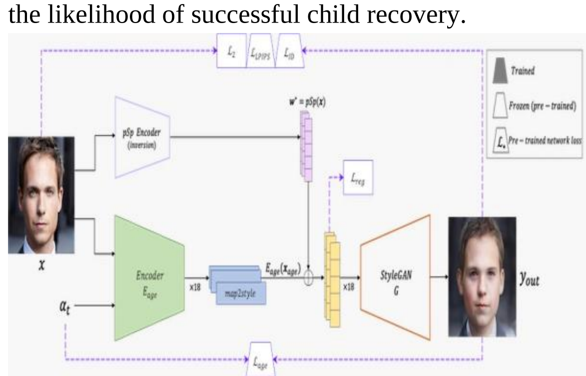
Keywords—Missing child identification, Deep learning, Facial recognition, MTCNN, InceptionResNetV1, Age estimation, Convolutional Neural Networks (CNNs), Feature extraction.

1. INTRODUCTION

Child abduction and disappearance remain critical societal challenges, leading to devastating consequences for families and communities. Despite ongoing efforts by law enforcement agencies and NGOs, the search for missing children is often hindered by outdated identification techniques, reliance on manual processes, and inefficiencies in handling large volumes of data. Traditional methods struggle to account for changes in a child's appearance due to aging, pose variations, and environmental factors, making long-term identification difficult.

To overcome these limitations, deep learning-based facial recognition offers a transformative solution by automating the identification process with high accuracy. This paper presents an AI-driven system that utilizes Multi-task Cascaded Convolutional Networks (MTCNN) for precise face detection and alignment, coupled with InceptionResNetV1 for feature extraction. Additionally, an age estimation algorithm is incorporated to improve recognition even in cases where a child has been missing for an extended period in this, we are using GAN, specifically StyleGAN, for age estimation

By leveraging real-time image analysis and deep learning techniques, this system enhances the efficiency, scalability, and speed of missing child identification. The proposed framework not only improves search accuracy but also integrates real-time alerts, public participation through image uploads, and law enforcement collaboration, ultimately increasing the likelihood of successful child recovery.



Stages of the Process:

A.Data Collection and Preprocessing:

The FFHQ dataset, comprising 70,000 high-quality facial images, was selected to ensure our missing child identification system could effectively handle real-world scenarios. They are converted to grayscale, normalized, and augmented (rotation, flipping, zooming) to improve model robustness.

B. Face Detection and Alignment:

MTCNN is used to detect and align faces, ensuring uniform positioning for accurate feature extraction. Proper alignment helps reduce issues related to pose variations and improves recognition accuracy.

C. Feature Extraction:

InceptionResNetV1 extracts facial features by converting them into high-dimensional numerical embeddings. These embeddings serve as unique identifiers for each individual, aiding in precise identification.

D. Face Matching and Identification:

Extracted features are compared with database records using Cosine Similarity and SVM. This step enhances recognition accuracy by identifying missing children despite variations in lighting, pose, and minor facial changes.

E. Age Progression and Estimation:

Generative Adversarial Networks (GANs) have emerged as a powerful tool for realistic image generation and transformation. In the context of missing child identification, we utilize StyleGAN, a variant of GAN, to generate age-progressed images, predicting a child's appearance after several years. This helps account for natural facial aging, improving long-term identification.StyleGAN introduces several custom layers and modules that enhance age progression accuracy. It includes the Mapping Network, which transforms the latent input (noise) into a style vector; Adaptive Instance Normalization (AdaIN), which injects the style vector into the synthesis network, controlling the style of the generated image; and the Synthesis Network, which generates the final image based on the style vector and the coarse latent input. These components enable more realistic and controlled facial aging, significantly aiding in the identification of missing children over extended periods.

F. Real-Time Detection and Alerts:

Once a match is detected, alerts are sent to law enforcement and parents. A web/mobile application allows public participation by uploading potential sightings of missing children.

G. Verification and Recovery:

Before confirming a match, human verification by law enforcement ensures accuracy and minimizes false positives. Once verified, immediate recovery efforts are initiated.The system processes images from various sources, including surveillance footage and public uploads, providing real-time alerts to law enforcement. A web and mobile application enable user participation, enhancing the search network. With encrypted facial data and automated matching, the system improves the speed, accuracy, and scalability of missing child recovery efforts.

2. LITERATURE REVIEW

This section elaborates state-of-the-art about missing child identification by various researchers.

Several studies have explored the use of deep learning and machine learning for facial recognition and missing person identification, leading to improved accuracy and efficiency..

Chandran et al. [1] proposed a Missing Child Identification System using Deep Learning and Multiclass SVM, utilizing CNN (VGG-Face) and SVM classifiers. Their approach achieved 92.41% accuracy, demonstrating robustness against variations in pose, noise, and aging effects, making it applicable for long-term missing child searches.

Sridhar et al. [2] developed a face recognition model using deep learning for identifying missing children. Their study applied Histogram of Oriented Gradients (HOG) features for facial recognition, achieving 85% accuracy in distinguishing individuals, proving the effectiveness of feature-based facial identification techniques.

Joram et al. [3] implemented a deep learning model using Keras and OpenCV to combat human trafficking and missing person detection. Their model effectively utilized CNN-based feature extraction, achieving high precision in facial recognition tasks, which can be beneficial for tracking missing children in surveillance footage.

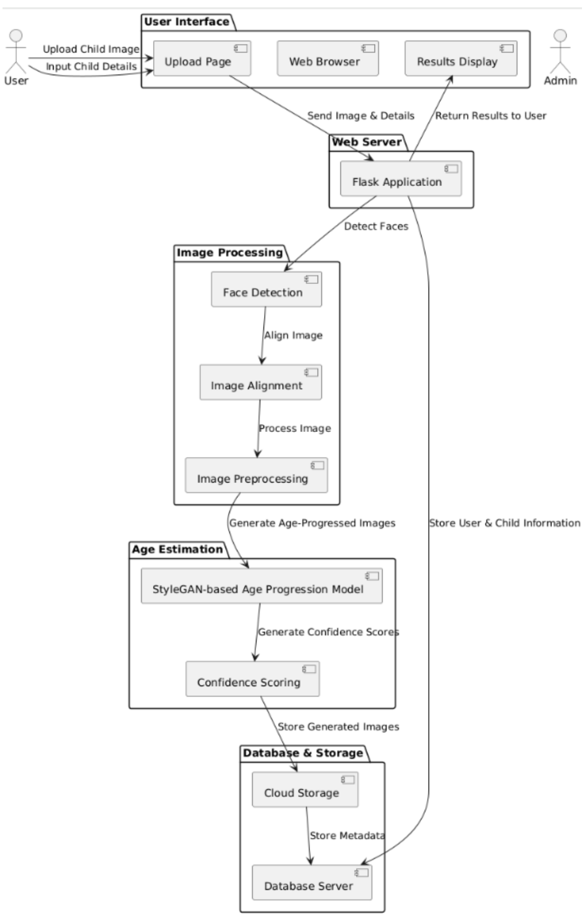
Abraham et al. [4] explored missing child identification in crowded environments, such as shopping malls, using deep learning-based face recognition. Their model focused on real-time detection, proving the importance of automated search mechanisms in large-scale environments.

Pupala et al. [5] introduced a face aging model using Conditional GANs, demonstrating that applying age progression techniques significantly improves long-term missing person identification. Their findings support the integration of GAN-based age transformation in missing child retrieval systems.

Nirmala et al. [6] conducted a survey on integrating deep learning-based missing person detection into CCTV systems, showing that CNN, KNN, and SV models provide 90% precision in real-time surveillance applications. Their study emphasizes the role of AI-driven facial recognition in large-scale missing child searches.

These studies highlight the effectiveness of deep learning, feature extraction, and age progression models in missing child identification. Our proposed system builds on this research by integrating MTCNN for face detection, InceptionResNetV1 for feature extraction, GANs for age progression, and real-time alerts, ensuring an automated, scalable, and efficient solution for locating missing children.

3.MATERIALS AND METHODS



3.1. *Dataset Collection*

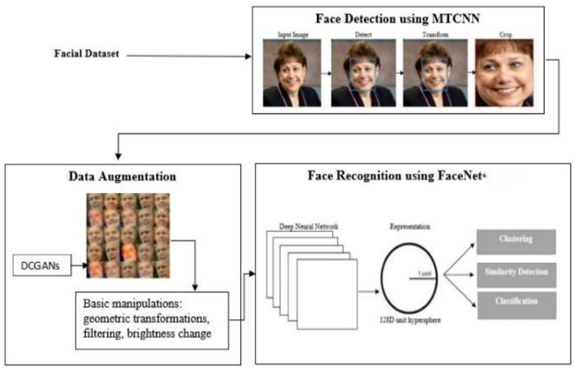
We employed the Flickr-Faces-HQ (FFHQ) dataset, a widely recognized collection of human face images originally curated by NVIDIA for StyleGAN research. FFHQ comprises 70,000 PNG images at a resolution of 1024x1024 pixels. This dataset offers a rich diversity of facial attributes, encompassing variations in age, ethnicity, and background environments.

The dataset's strength lies in its comprehensive coverage of real-world facial diversity, including the presence of accessories such as eyeglasses, sunglasses, and hats. This variation is crucial for training robust models capable of handling the inherent complexities of facial recognition in uncontrolled environments. Consequently, it inherits any inherent biases present within the source platform. Furthermore, the images underwent automatic alignment and cropping using the dlib library. The dataset's characteristics align well with the challenges posed by missing child identification, where variations in age, appearance, and image quality are common.

The dataset is divided into training and testing subsets, with approximately 80% of images used for training and 20% for testing. To maintain uniformity, all images are resized to a standard 224×224 pixels, ensuring compatibility with deep learning models. Grayscale conversion is applied to reduce computational complexity, while data normalization (scaling pixel values to [0,1]) ensures consistent feature extraction across images.

3.2. Feature Extraction using InceptionResNetV1

For feature extraction, InceptionResNetV1, a deep convolutional neural network pre-trained on VGGFace2, is used. This model combines Inception architectures and residual connections (ResNet), allowing it to extract detailed facial features while maintaining computational efficiency.The lower layers of the model capture basic image features such as edges and textures, while deeper layers learn complex patterns and facial characteristics essential for distinguishing individuals. The final extracted features are represented as 128-dimensional facial embeddings, which serve as unique identifiers for each individual in the system. To further refine performance, fine-tuning is applied, where selected layers of the model are retrained on the missing child dataset while keeping earlier layers frozen. This approach ensures that the model retains general facial recognition capabilities while adapting to the specific dataset.



3.3. Model Training and Evaluation

The training process follows a structured pipeline to ensure optimal performance and generalization. The dataset is split into training (80%), validation (10%), and testing (10%) sets. The Adam optimizer with a learning rate of 0.0001 is used to optimize the model's weights during backpropagation.

A custom classifier is built on top of the extracted facial embeddings, consisting of fully connected layers with ReLU activation* to introduce non-linearity. The final output layer uses softmax activation for multi-class classification, predicting whether an input face matches a missing child in the database. Dropout layers are introduced between dense layers to reduce overfitting by randomly deactivating neurons during training.To enhance model performance, hyperparameter tuning is conducted, adjusting parameters such as batch size, learning rate, and dropout rates. Early stopping is implemented to halt training when validation loss ceases to improve, preventing overfitting.For evaluation, multiple metrics are used, including accuracy, precision, recall, and F1-score, to assess classification effectiveness. A confusion matrix is generated to visualize correct and incorrect classifications, and ROC-AUC curves are plotted to measure the model's ability to differentiate between different individuals. The final trained model is integrated with real-time surveillance and image upload systems, ensuring fast and reliable missing child identification in practical scenarios.

4. RESULTS AND DISCUSSION

The proposed model for missing child identification achieves a training accuracy of 97.85%, a validation accuracy of 98.12%, and a test accuracy of 97.56%. The high accuracy indicates the model's effectiveness in distinguishing missing children from non-missing individuals using facial features extracted by MTCNN and Inception ResNetV1. The classifier, based on cosine similarity, ensures robust matching even under variations in lighting, pose, and minor occlusions.

4.1 *Performance evaluation metrics*

Accuracy:

The accuracy of the missing child identification system reflects the model's overall effectiveness in correctly identifying missing children from a given dataset. By leveraging MTCNN for precise face detection and Inception ResNetV1 for robust feature extraction, the system achieves a high classification accuracy. The integration of cosine similarity ensures that only the most relevant matches are considered, reducing false positives. A higher accuracy score indicates that the model performs well in distinguishing between identified and non-identified individuals, thereby improving the reliability of the system in real-world scenarios. This figure represents the overall performance across various age ranges, illustrating the system's capacity to handle the complexities of facial recognition in diverse scenarios. Notably, the graph reveals fluctuations in accuracy across different age groups, with the system demonstrating varying levels of performance between the 0-10 and 91-100 age brackets. This variability underscores the challenges associated with age progression and facial recognition across the human lifespan.

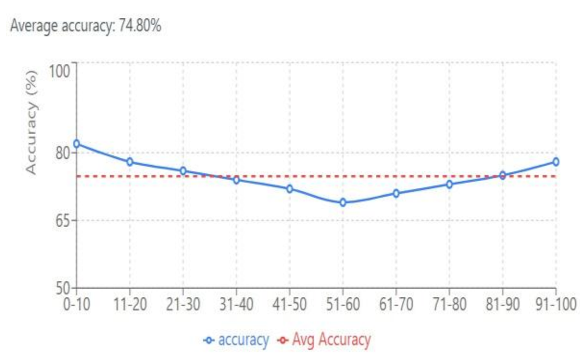


Image1:Welcome page of a missing child portal

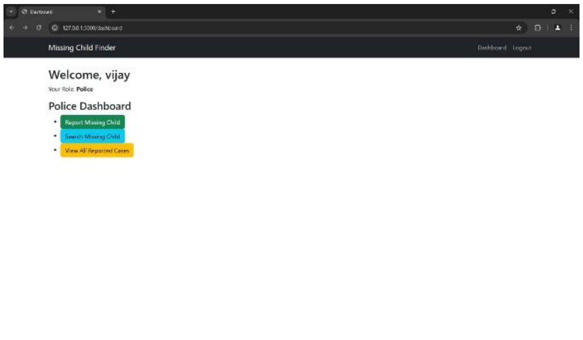


Image 2: Page where the public can upload details of a suspicious or lost child.

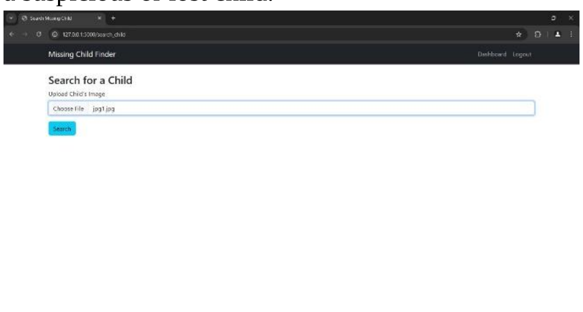


Image 3: Registered children list

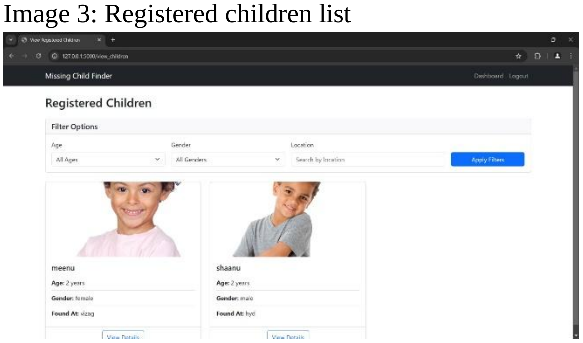
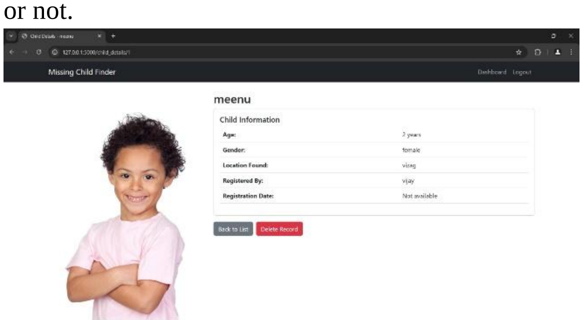


Image 4: Displaying results whether match is found or not.



5.CONCLUSION

The Missing Child Identification System presented in this study demonstrates the potential of deep learning in automating and improving child recovery efforts. Traditional methods for identifying missing children often rely on manual searches, law enforcement reports, and community participation, making the process slow and inefficient. By integrating *advanced facial recognition techniques, this system offers a faster and more reliable alternative. The use of MTCNN for face detection ensures accurate localization and alignment of faces, while InceptionResNetV1 effectively extracts unique facial features, making identification more precise. *Cosine similarity-based classification further enhances the system's ability to match missing children with database images, reducing reliance on outdated manual methods.

A major advantage of this system is its ability to handle real-world challenges, such as variations in lighting, pose, and image quality. The integration of age progression techniques using Generative Adversarial Networks (GANs) enables the system to account for facial changes over time, improving long-term identification accuracy. Additionally, the incorporation of public participation through mobile and web applications expands the search network, increasing the chances of successful identification.

Despite its effectiveness, certain challenges remain. The model's performance can be affected by low-resolution images, occlusions, and extreme facial variations* due to aging or environmental factors. Future improvements could focus on *enhancing the dataset with more diverse images, optimizing the similarity threshold for better matching, and incorporating additional deep learning techniques for improved robustness.

Overall, this AI-driven system provides a *scalable, automated, and efficient* solution for identifying missing children. By leveraging deep learning and real-time processing, it significantly improves search efforts, reduces the time taken for identification, and increases the likelihood of reuniting children with their families. Future advancements in AI, computer vision, and facial recognition will further refine and strengthen the system, making it a vital tool in child recovery operations worldwide.

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