Detection of Eloped Juvenile Using AI*

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Abstract:- The issue of juvenile individuals running away or eloping is a serious and ongoing problem that can have significant consequences for the safety and well-being of the juveniles involved, as well as for their families and communities. In this project, we propose a system for detecting and reuniting missing juveniles using artificial intelligence (AI) techniques. The system utilizes data uploaded by the authorities in the juvenile home through a website, in which every juvenile has an individual profile that is used to identify and locate missing juveniles in real-time. By applying HOG feature, Face Landmark Estimation, CNN, and SVM Classifier to this data, we are able to train the model with each juvenile. When the public encounters a suspicious child, they can take a photo and send it to the concerned authorities. Then the authorities can verify the juvenile through an application developed using the trained model. The face recognition model in our system find a match in the database with the help of face encoding. It is performed by comparing the face encoding of the uploaded image to those of the images in the database. If a match is found, it will be notified to the police station along with the location of where the juvenile is found in order to facilitate their safe return. Our system represents a promising approach to addressing the issue of missing juveniles. It has the potential to greatly improve the speed and efficiency with which they are located and return them to the juvenile home. This paper suggests a framework that would help the police and general society to identify missing juveniles by utilizing a hybrid CNN model. The proposed CNN model have achieved an accuracy of 95%.

Keywords:- *Juvenile; CNN; Face Recognition; HOG;*

I. INTRODUCTION

A total of 31170 cases were reported against minors nationwide in 2020, which represents a 4.7% increase over that year's 29,768 cases[1]. The majority of them, 28,539 in total, or 76.2 percent, belonged to the 16 to 18 age group[2]. Examining CCTV footage and other evidence is the best course of action in these situations. Once more, this can take a lot of time, and keeping up with it might be difficult considering how many people disappear every day. It is important to have systems in place to quickly locate and return missing juveniles to their concerned authorities, as their absence can have serious consequences for their safety and public well-being. However, as we mention, there are currently no adequate digital systems in place for reporting and investigating missing juveniles. This can make it difficult for police and authorities to find missing juveniles who are below the age of 18 and can also make it more difficult for law enforcement to investigate cases of missing juveniles by traditional manual methods. Existing methods for finding missing juveniles, such as publishing newspaper ads and pasting posters, can be useful in some cases, but they may not be sufficient to quickly and effectively locate missing juveniles in all cases. In addition, these methods may not be effective and these cases require special attention compared to normal person missing cases. There may be a need for more comprehensive and effective systems for finding missing juveniles, particularly in cases where the juvenile's absence may be related to criminal activity or other potential dangers. Such systems could utilize advanced technologies and data analysis techniques, similar to those used in systems for finding missing juveniles, in order to quickly and accurately locate missing juveniles and return them safely to the concerned authorities.

Number of works have been reported for detecting Juvenile delinquency but a software exclusively designed for eloped juvenile still an open issue are not prescribed. This problem can be reformulated as automated face recognition system. A lot of researches are experimented for identification of faces. Earlier works are focused on traditional feature extraction and classification using machine learning techniques [3,4,5]. With the advent of convolutional neural networks, researches are centered on deep learning. In this paper, we are presenting a hybrid model which uses a combination of deep features and machine learning classifier for the accurate identification of eloped juveniles.

II. PROPOSED SYSTEM

The overall flow of the application pipe line is depicted in Fig. 1. The police officers/public can upload the eloped persons picture and can identify whether it is juvenile or not. The juvenile registration has to be done by the authorities of the juvenile home. The key components of the model is detailed in the subsequent sections.

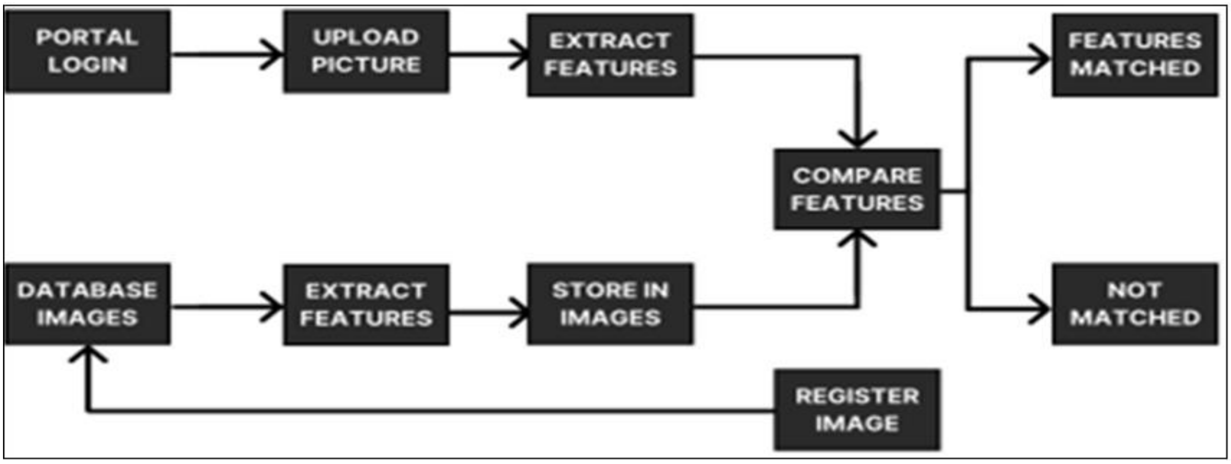

Fig 1 Flow of Work

A. Pre-processing

The input images are resized to a fixed size to ensure consistency in feature extraction. Resizing the images helps in normalizing the spatial dimensions, making them suitable for subsequent processing steps. The input images are of RGB type, so the resized images are converted from color to grayscale. Grayscale images contain intensity values, which simplify subsequent feature extraction processes and reduce computational complexity. To enhance the local contrast of the grayscale images, contrast normalization techniques are employed. This step aims to make image regions with varying illumination conditions more distinguishable, thus improving the discriminative power of the extracted features. In order to normalize the local image regions, apply a process called local normalization. This technique helps to minimize variations in illumination and shading across different regions of the image, thereby improving the robustness of feature extraction.

B. Histogram of Oriented Gradients (HOG)

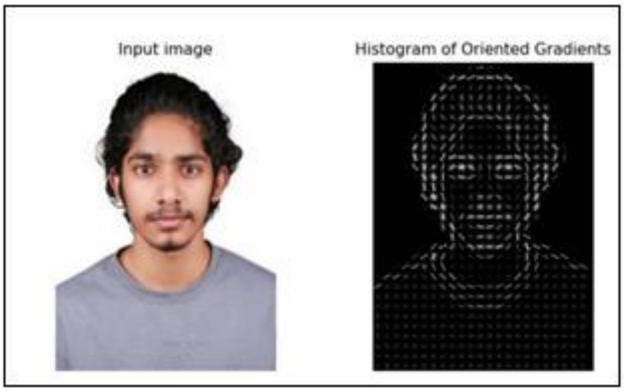

Fig 2 Sample Results after Applying HOG

The Histogram of Oriented Gradients[6] is a feature extraction technique commonly used in computer vision tasks, particularly in object detection. It is based on the intuition that local object appearance and shape information can be effectively represented by the distribution of gradient orientations within an image (shown in Fig 2). The HOG algorithm works by dividing an image into small cells and calculating the gradient orientation within each cell. The gradient is computed by taking the derivative of pixel intensities along the x and y axes. These gradient magnitudes and orientations are then used to construct histograms that capture the distribution of gradient orientations within each cell. The histograms are further normalized to account for variations in lighting conditions and contrast. By capturing the local gradient information, HOG is able to capture important edge and shape features of objects within an image. This makes it particularly effective for image detection tasks, where the goal is to identify specific objects or regions of interest within an image.

C. Integration of HOG with MTCNN

MTCNN (Multi-task Cascaded Convolutional Networks) is a popular deep learning based algorithm[7] for face detection and facial landmark localization. HOG is utilized within the MTCNN framework to enhance the accuracy and robustness of face detection. In MTCNN, HOG is employed in the initial stage of the cascade to generate candidate face regions. The algorithm uses a sliding window approach, where different scales and aspect ratios of the HOG features are evaluated at multiple locations in the image. These HOG-based detections serve as initial proposals for potential face regions. Subsequently, the MTCNN algorithm employs deep neural networks to refine and verify these candidate regions. The deep networks learn more discriminative features and further classify the regions as either face or non-face. In addition to face detection, MTCNN also utilizes HOG for localizing facial landmarks, such as eyes, nose, and mouth. By incorporating HOG in MTCNN, the algorithm benefits from the robustness and efficiency of HOG in generating initial face region proposals. This enables MTCNN to handle variations in lighting conditions, pose, and occlusions, providing an effective solution for accurate face detection and facial landmark localization. MTCNN have proposal net,refine and output stages to detect faces of individulas. The output stage identifies face, nose eyes etc

D. Integration of Facenet with MTCNN

The output of MTCNN is given as input to Facenet[8]. It comprises Convolution layers, Normalization layer, Inception modules, Fully connected layer and finally embedding layer. The convolutional layers use filters (also known as kernels) to convolve over the input image, capturing different features at multiple scales. Normalization layers usually ensure that feature vectors have a consistent scale and direction. Inception Modules are designed to capture various types of features, including fine-grained details and more global facial features. The fully connected layer performs dimensionality reduction and produces feature vectors with a fixed size for each input face image. The fully connected layer is followed by an embedding layer, which outputs a feature vector or embedding for each face. These embeddings are the representations of the input face images in a high-dimensional space.

E. Support Vector Machine Classifier

Support Vector Machine (SVM) classification[9] is a powerful machine learning algorithm widely employed for solving binary and multiclass classification problems. SVM operates by identifying a hyperplane that best separates data points of different classes in a feature space using support vectors. The key innovation of SVM is its ability to find the optimal hyperplane that maximizes the margin between classes, making it a robust choice for cases with complex decision boundaries. The facial features extracted from faces are given to the SVM model for training(x_i). Given a set of training data points, where each data point is represented as (x_i, y_i), where x_i is the feature vector of data point i, and y_i is its corresponding juvenile label, SVM aims to find a hyperplane that best separates the data into two classes.

III. RESULTS AND DISCUSSIONS

The website and an app is developed using HTML, CSS, JavaScript, Location API, Django, and PostgreSQL.The system will utilize a website where police officers/juvenile authorities can upload the photos of each juvenile brought to the juvenile home, creating individual accounts for them. Additionally, an app will be developed, allowing anyone who notices a suspected eloped juvenile in public to upload their photo for potential identification.

- Preprocessing and Feature Extraction: Before feeding the data to the SVM classifier, we perform preprocessing steps on the input images. This includes converting the color space from BGR to RGB to ensure compatibility with the facial recognition models used. Additionally, we apply the MTCNN (Multi-task Cascaded Convolutional Networks) algorithm incorporated with HOG to detect and extract faces from the input images accurately.
- Face Embedding Extraction: After obtaining the facial regions from the input images, we pass each face through the Face Net model to extract high28 dimensional feature embeddings. The Face Net model utilizes a deep convolutional neural network architecture to map faces into a feature space where facial similarities are well-defined.
- SVM Training: Once we have extracted the face embeddings, we utilize a labeled dataset containing facial embeddings of known individuals to train the SVM classifier. The training process involves optimizing the SVM model's parameters and finding the best hyperplane that separates the different classes of face embeddings.
- SVM Prediction: In the prediction phase, we utilize the trained SVM classifier to classify new face embeddings. Given a test face embedding, we pass it through the SVM model and obtain the predicted label. The SVM model assigns a class label to the test embedding based on the learned decision boundaries from the training phase.
- 5.Thresholding: To ensure reliable recognition, we incorporate a thresholding mechanism. The maximum probability score (obtained from the SVM classifier's predicted probabilities) is compared against a predefined threshold value (THRESHOLDFACENET). If the maximum probability is above the threshold, the predicted label is considered valid. Otherwise, the label is set to "unknown".
- Visualization and Result: Finally, we visualize the results by drawing bounding boxes around the detected faces in the input images. The predicted label, along with its corresponding probability score, is displayed on top of the bounding box. Recognized individuals are highlighted with a green bounding box, while unknown individuals are marked with a red bounding box.

A. Qualitative Results

Fig. 3 depicts the screenshot of home page of the designed app.Through this App, the authorities can register the details of juveniles (Fig.4) and also can verify whether the reported person is juvenile or not. Fig. 5 shows the results obtained from the trained model.

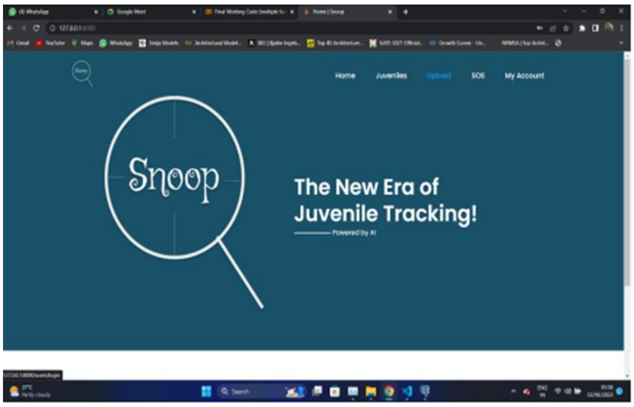

Fig.3 GUI of Developed App

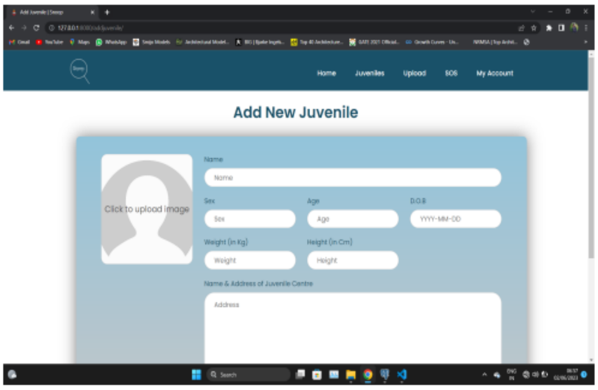

Fig 4 Registration Form

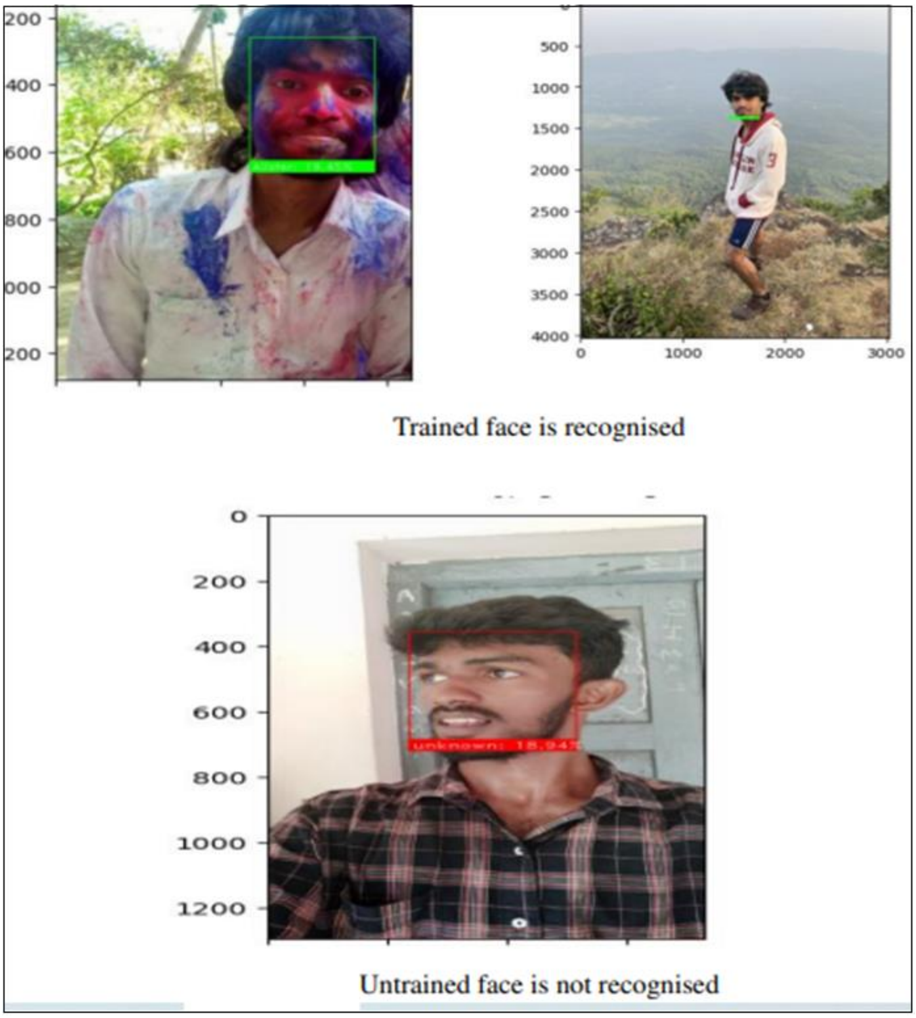

Fig 5 Screenshots of the Results

B. Quantitative Results

We have performed experimentation on a dataset with 1000 persons each persons with five images. The data set is split into train validation and test .We have trained and tested on the models - HOG+SVM, HOG+Random Forest, HOG+MTCNN, VGG 16 and HOG+MTCNN+SVM. The accuracies obtained are depicted in Fig.6. It was found that HOG+MTCNN+SVM combination produced an accuracy of 95% compared to other models.

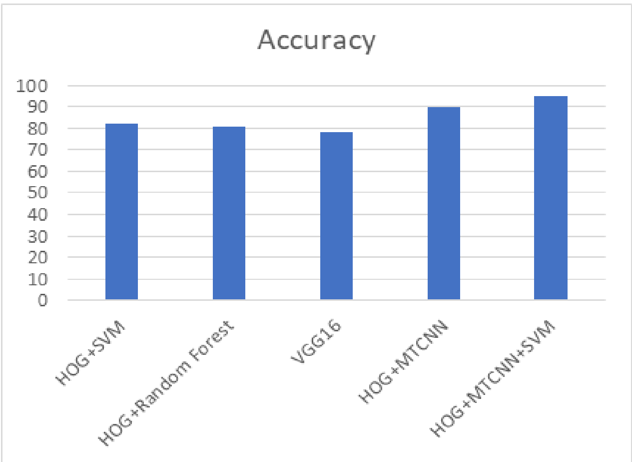

Fig 6 Accuracy Graph

IV. CONCLUSION

Face recognition and tracking systems already exist, this paper specifically targets the detection and tracking of eloped juveniles. Tracking eloped juveniles poses unique challenges compared to general face recognition and tracking systems. The project takes into account age-related factors that are specific to juveniles. As children and adolescents are more vulnerable, their safety and protection are of utmost importance. The system will be designed to handle sensitive data in compliance with legal and ethical guidelines to ensure privacy and safeguard the welfare of the juveniles involved. The work actively collaborates with law enforcement agencies to understand their specific requirements and challenges in tracking eloped juveniles. By working closely with these agencies, the system can be tailored to meet their needs and integrate seamlessly into their existing workflows, enabling efficient and effective utilization of the technology in real-world scenarios.

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