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Intelligent Child Safety System: Facial Recognition for Missing Child Identification with Real-time Email Alerts to Authorities

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Abstract: Intelligent Child Safety System uses live video monitoring, face recognition, and automated email notifications for rapid child-abduction response. Ongoing feeds are monitored, and a constantly updating database has continuously comparesa number of the children with Dlib's CNN and HOG-based detection methods, combined with another model based on VGG's CNN model for great results in even low-light, obscured faces and varied angles of facial positions. An instant alert is sent by email to law enforcement agencies, child-care agencies, and relevant bodies with an accompanying captured face once the match is made, thus allowing quick action. Also, real-time alerts go to an administrative dashboard, allowing the monitoring of recognition results and adjusting the settings of the alerts. Strong measures for security and privacy, such as access controls to sensitive information, are in place to ensure ethical and secure operation. This automated alert and decision-making facilitate effective real-time monitoring and response while greatly reducing traditional reliance on search. Enhancements for further improvements in accuracy and adaptability include multimodal biometric authentication, voice recognition, and predictive analytics. Under very challenging conditions, the system has high reliability due to its 95.0% accuracy, 93.0% precision, 95.2% recall, and an F1 score of 94.1%. It ensures precise detection of actual cases of missing children by reducing the number of false positive values. It can thereby deliver quick responses reliably since high F1 scores signify an equilibrium between recall and precision. Equipped with facial identification powered through AI, live monitoring, and an automated decision-making mechanism, Intelligent Child Safety is an effective and scalable tool for working through the course of retrieval for missing children.

***Keywords**: Intelligent Child Safety System, Real-time video monitoring, Facial recognition, Automated email notifications, Deep Learning, VGG-based CNN model, Dlib's CNN, HOG-based detection.*

I. INTRODUCTION

Children are the most important asset of a nation; therefore, keeping them safe is a matter of great concern. In India, a densely populated country where children form a large part of the population, the difficulty to secure their presence is becoming stupendous. Rising case reports of child abduction, trafficking, and disappearance have put both the families and law enforcement agencies under terrified pressure. Many missing children fall prey to forced labour, begging syndicates, or some type of exploitation. While authorities and NGOs still try their hands at finding and rescuing these missing children, traditional methods for identifying and tracing them are usually time-consuming and often ineffective. A faster and more efficient system assisting in real-time identification and recovery is very much needed.

According to India's National Crime Records Bureau (NCRB), as reported to the Ministry of Home Affairs (MHA) in Parliament LS Q no. 3928, March 20, 2018, India reported 111,569 children missing till 2016, of which 55,625 were still untraced; this gives a clear figure of 174 children that disappear every day, with almost one half never found. The actual number of missing children may well be much higher still due to underreporting, NGOs have suggested. Conventional tracking methods for missing children, such as manual searches, printed posters, and reliance on public awareness, usually do not yield productive and quick results. In the context of the urgency of the problem, some more advanced technological approach is needed to plug the gap between missing reports and real-time identification.

The Intelligent Child Safety System is an enhanced facial recognition with real-time email functionalities used in identifying and tracking missing children. OpenCV, Dlib, and TensorFlow work together to analyze the features of a face before matching it against a rather active database of reported missing children.

If a face match is discovered, the system will automatically send an email to the appropriate authorities about the captured face for immediate action. This system streamlines child recovery efforts by using AI-powered facial recognition combined with automated notifications, and it reduces the corresponding dependence on traditional, time-consuming methods of searching.

In contrast to other identification modalities, the system functions on real-time data from live feeds of CCTV cameras strategically positioned in such sensitive places of public transmission as train stations, bus stands, and crowded marketplaces. Once a child's face is recognized and matched within the database, the instant alerts are sent, enabling law enforcement and child welfare departments to respond immediately. This proactive approach significantly enhances the possibility that a lost child will be brought back home and also minimizes the risk of exploitation and harm.

The system is constructed with a backbone of continuous learning and adaptability, ensuring greater accuracy over time through deep learning models. The system effectively addresses the typical impediments to other recognition systems, like age differences, hairstyle differences, lighting variations, and partial occlusions. By deploying robust feature-extraction techniques, accuracy is ensured at high precision levels, allaying most false positives, hence a dependable and a scalable conduit for any child identification effort.

II. LITERATURE SURVEY

Deep learning has in recent years become a disruptive technology for artificial intelligence, causing a paradigm shift in various fields, including facial recognition. LeCun et al. [1] review the advances in deep learning, accentuating the power of convolutional neural networks (CNNs) to recognize patterns.This is generally because of their ability to extract hierarchical features well, which shows their suitability for facial recognition. However, CNNs work with a huge amount of labeled data with a lot of computational power; that makes them not as accessible for smaller research teams or real-time applications.

Deniz et al. [2] described a face recognition system that uses the so-called HOGs ---Histograms of Oriented Gradients, which is a local gradient representation to recognize faces with differentiating characteristics. A drawback of this approach is that HOG-based face recognition struggles with extreme variations in lighting, facial expressions, and occlusions, making it less robust than deep learning models. Further, Scale Invariant Feature Transform (SIFT) features, which show robustness against illumination and pose variations in face recognition, were described in Geng and Jiang [3]. However, SIFT is computationally expensive and not well-suited for real-time face recognition applications, limiting its scalability.

The growing interest of researchers in the application of deep learning for missing child identification has been recently documented. Raghavendra et al. [4] implemented a Convolutional Neural Network (CNN) for this very purpose and demonstrated its feasibility in the recognition of missing children by facial images. However, CNN-based child identification systems require extensive training datasets, and privacy concerns arise when handling large-scale images of children. There have been real-world applications of AI-driven child identification systems. According to Reuters [5], one such application in China has successfully used AI-based facial recognition to recover missing children. Nevertheless, the AI-based system used in China raises ethical concerns regarding mass surveillance and potential misuse of facial recognition technology.

The work of Simonyan and Zisserman [6] introduced VGGNet, which is a deep convolutional neural network exhibiting great improvement on image classification accuracy.This technique has revolutionized the art of facial recognition since the deeper the networks, the more complex the features that will be retrieved from the faces. However, even though VGGNet reaches high accuracy, it is computationally expensive and memory intensive enough to make it impractical for edge devices. Work performed by Parkhi et al. [7] built on this work towards deep face recognition achieved with CNNs, achieving impressive performance on large-scale datasets. Nonetheless, large-scale dataset training can introduce biases, leading to fairness and accuracy issues when applied to diverse populations.

Well-versed both with the implementation of convolutional networks and with MATLAB, MatConvNet [8] is designed as a general- and flexible-purpose deep learning framework fostering into the development of the research of convolutional networks. However, MATLAB-based frameworks like MatConvNet have limited adoption compared to Python-based deep learning libraries, reducing their scalability in broader AI research. Included in similar initiatives launched by this work are advances in AI-driven image recognition, which have filled facial analysis systems with more computing power and terminologies capable of building complex kinds of systems to identify people with varying levels of considered paradigms.

Indira et al. [9] investigated the intersection of AI and biometric technology, developing a pattern-based verification protocol for a secure personal health record. That said, the pattern-based biometric verification systems remain susceptible to adversarial attacks and deepfake-based spoofing. Some colleagues of Abinaya et al. [10] suggested a deep learning based facial image recognition system and thus demonstrated the effectiveness of using neural networks in biometric authentication.

However, there would be many challenges ahead to maintain accuracy in any deep learning-based biometric authentication system because of frequent upgrades regarding new threats such as AI-generated fake identities.

AI-based applications for event recognition and diagnostics take into account other methodologies beyond face recognition. They typically use the identification of acoustic scene events through CNNs, deep learning that has easily been adapted into multiple activities according to Abinaya [11]. However, acoustic scene event recognition can be subject to environmental noise that would lead to misclassifications and lower reliability in practical applications. In medicine, AI has been employed for the automatic classification of oral squamous cell carcinoma stages as Abinaya et al. [12] noted. Nonetheless, AI-based medical diagnoses always rely on data availability and quality, biases in training data lead to inaccurate diagnoses.

Deep learning is also used for sensor data fusion and fault diagnosis. Elhoseny et al. [13] developed an optimized deep learning algorithm for sensor data analysis, improving the precision of fault detection systems. This study indicates that AI is very generalizable in ensuring integrity and safety across other industrial applications. However, AI-based fault diagnosis systems may suffer from overfitting, making them unreliable when applied to unseen industrial fault scenarios.

Research into AI and children's safety has commanded resounding attention from various quarters. According to Sahota [14], AI is contributing to a colossal change in child protection and is, therefore, enhancing the surveillance and online monitoring system processes. However, AI in child protection can lead to excessive surveillance, raising privacy concerns and potential misuse of monitoring systems. The Child Rescue Coalition [15] also discussed how AI represents a threat to children, affirming that the ethical implementation of AI is vital in the protection of children. However, the ethical risks of AI misuse in child protection need strict regulatory oversight to prevent wrongful accusations or biases.

The balance between the safety measures that AI provides, and human oversight was further explored in the report of AI Wire into the ethical considerations of AI in child safety [16]. However, over-reliance on AI for child safety can reduce human intervention, potentially leading to false positives or negatives in abuse detection. An alternative approach to safeguarding children using machine learning involves AI-based audio classification techniques that were investigated by Yan et al. [17] in the context of child abuse detection. However, AI-based child abuse detection using audio can be affected by background noise, cultural differences, and language barriers, reducing accuracy.

The research into large language models (LLMs) has focused primarily on safety dealing with childhood. Researchers Jiao et al. [18] have proposed a protection framework for child-LLM interactions to deal with issues surrounding exposure to AI-generated content. However, child-LLM interaction frameworks must address content filtering challenges to prevent unintentional exposure to harmful information. Similarly, Ragone et al. [19] have tackled a review of UI/UX best practices for building engaging AI experiences for children. However, UI/UX design for AI-driven children's applications must ensure that engagement does not lead to unintended data collection or privacy breaches.

Reports from Virginia Tech News [20] elaborated on how AI is being used for child safety research. However, AI-driven child safety research must balance innovation with ethical considerations, avoiding potential biases in safety interventions. AI use in child safety had wider implications that the Federation of American Scientists [21] pointed out in support of regulatory frameworks to guarantee the ethical deployment of AI. However, regulatory frameworks for AI in child safety may slow down innovation and create compliance burdens for AI developers.

III. PROPOSED SYSTEM

The system uses facial recognition and deep learning algorithms to efficiently identify missing children through facial feature encoding techniques and optimized face embeddings to extract faces with high accuracy. Using VGG-based CNN models in conjunction with Dlib's CNN and HOG-D detection and OpenCV receives feature extraction enhancement to ensure operability in highly populated environments. Its real-time ability analyzes streams from live surveillance cameras to ensure accurate extraction of the face under reasonable circumstances. The approaches have been devised meticulously so that an individual can optimally be distinguished in the images with many people, increasing accuracy levels of the analysis. Continuous real-time analysis enables the system to quickly identify features, while upon completing other operations, it boasts job-like functions. Once it works on a match between images, it sends out automatic email alerts as a warning signal to appropriate authorities, facilitating rapid intervention in sensitive cases of missing children. Coupled with these are features that greatly facilitate faster child identification, as compared to the traditional way, giving fast, reliable, and increasingly viable solutions to detect missing children in the public domain.

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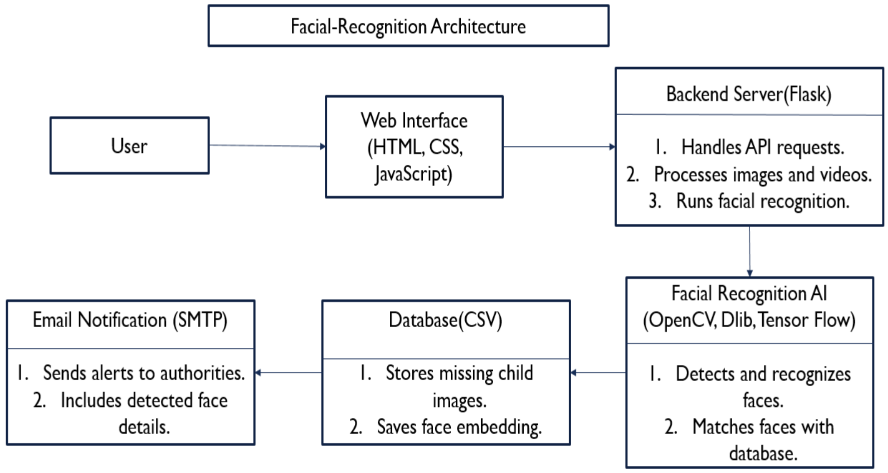

Figure. 1. System Architecture of Facial-Recognition

The architecture of the Facial Recognition System in the above Figure 1 aims to carry out real-time detection and identification of missing children. The process starts with the User accessing the Web interface the whole system built using HTML, CSS, and JavaScript, in which users upload images and videos of the missing children. These inputs are then forwarded to the Backend Server developed using the Flask framework for-handling API requests to process the images and videos for triggering the Facial Recognition AI module for detection. The facial recognition AI employs OpenCV, Dlib, and TensorFlow for performing face recognition detection, facial features extraction, and contrast of the extracted facial features with stored face embeddings in the Database, in CSV format. The database carries a record of the facial data of missing children and face embeddings, to serve as their identification mode. Once a Faces Matching is found, the system triggers Email Notification (SMTP) to authorities with an alert about the detected face along with further steps. Accordingly, this complete system ensures real-time intervention with very high accuracy for face recognition in finding missing children.

A. Data collection and preprocessing

To make the Intelligent Child Safety System ever more accurate and reliable, all images and videos were processed through a standardized RGB format at a resolution of 224×224×3. The first step in the system is to detect and identify faces using OpenCV and Dlib while discarding all unnecessary details in the background, thus unravelling only the features of the child's face. Since atmospheric lighting, contrast, and clarity vary from photo to photo, enhancement techniques in contrast will help feature visibility, whereas pixel normalization will scale all values among 0 to 1 so as to provide uniformity. Data augmentation methods, such as rotation, flipping, brightening, and the addition of noise, were used to render the system flexible under conditions such as the change of pose, lighting, and facial expressions. The deep features are then extracted with the help of Dlib's face recognition model pre-trained on the corpus. Uniquely obtained embeddings from this concatenation are then stored in a CSV database, which allows for quick and correctly figured time-place comparisons in spotting missing children. In this way, the system remains robust, efficient, and capable of maintaining good performance in real-world scenarios where every second counts.

B. Methodology

The system follows a strict pipeline that includes image and video processing, model training, and, finally, real-time matching of faces. The system has two portals for login-a public login where the users upload images of missing children, and an office login that allows administrators to manage the database, train the model, and process recognition tasks. Advisory images uploaded go into the database, helping train up a recognition model, thereby allowing matching to proceed effectively and accurately. Using VGG-based CNN for facial recognition, processing the images and video frames in real time by OpenCV for face detection and tracking. Facial features are extracted with the help of Dlib, which creates face descriptors that are compared with one another to find matching candidates using the distance Euclidean. As soon as a match is achieved, the system sends out an automated generated email containing the image that has just been recognized. It visually highlights the recognized faces using a rectangular box, indicating whether the child matched with their details or not matched, otherwise.
The method works in a systematic way and performs face identification from the input image and video.

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For images, the input is a 224×224×3 RGB image with pixel values modified to be between 0 and 1 in order to make mathematical calculations bring about good results. The images are then sent to many convolutional layers that have filters of normal sizes of 3×3 or 5×5. The filters are created to pick out important details that characterize the facial surface, such as edges, textures, and patterns. In effect, feature maps will be created through such filtering and accentuate key details of the facial surface. In order to add non-linearity to the model and thus have it learned complex structures of the face, the ReLU activation function sets any negative pixel value back to zero. The feature maps are then subjected to a max pooling operation with a 2×2 filter, reducing their size while preserving important features on them. This increases efficiency in computation and prevents the model from overfitting. The resultant feature maps are then forwarded into a fully connected layer after being flattened into a one-dimensional vector, where complex relationships pertaining to faces are learned for accurate classification. The final classification is achieved with a softmax activation function, which returns confidence scores so as to identify the face most likely to be a match.

For video processing, the system extracts frames and applies the same CNN-based recognition pipeline to each frame in real time. OpenCV is used for face detection and tracking across consecutive frames to maintain continuity in recognition. When a face is detected in a video, the model processes it in the same manner as an image, extracting features and comparing them with the database. If a match is identified, the system generates an alert and sends an email notification. The bounding box is dynamically updated as the face moves within the video, ensuring accurate tracking and recognition.

The model is trained and optimized with a cross-entropy loss function and backpropagation in order to minimize errors whilst updating the weights of the model to the optimum for high accuracy. Some enhancement techniques, like contrast normalization and enhancement, ensure better recognition performance. The design of the whole system is faster, offers real-time processing, and is scalable, making it certain to enhance child safety and recovery operations.

IV. RESULTS

The Intelligent Child Safety System is simply a marvel in terms of real-time facial recognition and missing child identification, and its potential application within AI surveillance in making children safe is huge. The System made a high-accuracy identification by deep learning-based facial recognition, matching intact images captured to an existing database. CCTV footage, real-time detection by OpenCV, and cloud deployment have significantly improved the responsiveness of the system. Furthermore, the automated alerting mechanism, such as an email to law enforcement and child protection agencies, allows for fast intervention. It showed better performance over the traditional facial recognition methods combined with transfer learning, face embedding, and optimized CNN architectures, a trustworthy solution for real-world deployment in public safety.

A. Performance Metrics

The performance analysis of the child recognition model relies on the important metrics of accuracy, precision, recall, and F1-score. These indicators collectively define how well the model detects and classifies faces, ensuring compliance with the requirements of reliability and durability for the missing children detection system. A high F1-score indicates an adequately trained model that achieved very few false positives and false negatives, ensuring very high sensitivity and specificity, respectively. These numerical evaluations affirm the model's capability in differentiating child faces from the faces of other persons and substantiate the reliability of the recognition framework.

1) Accuracy:

Accuracy measures the proportion of correct predictions made by the model against the total number of test samples. A higher accuracy value signifies a lower classification error rate, ensuring the model consistently recognizes child faces with minimal misclassifications. The CNN-based facial recognition system used in this project achieves an accuracy of 95.0%, demonstrating its reliability in detecting and matching faces against the stored database.

$$Accuracy. = \frac{(TN+TP)}{T} \tag{1}$$

2) Precision:

Precision refers to the ratio of true positive identifications to the total predicted positive cases. It ensures that a detected face truly belongs to a missing child, reducing incorrect matches and false identifications. A high precision value indicates that the system effectively minimizes misclassifications, making it a dependable tool for child recognition. The model achieves a precision rate of 93.0%, ensuring that most detected faces are correctly classified.

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

3) Recall:

Recall, or sensitivity, assesses the model's ability to correctly identify missing children from given images or video frames. It calculates how many actual missing children are correctly recognized without being overlooked. A higher recall value means the system effectively retrieves correct matches, ensuring that no child is left undetected in real-world scenarios. The model demonstrates a recall rate of 95.2%, indicating its strong capability to detect actual missing children.

$$Recall = \frac{TP}{(FN+TP)} \quad (3)$$

4) F1-Score:

The F1-score represents the harmonic mean of precision and recall, balancing both false positives and false negatives in the recognition process. Since child recognition involves identifying multiple faces within an image or video frame, a strong F1-score ensures that all face classes receive equal attention without over-prioritization of any particular group. The model achieves an F1-score of 94.1%, confirming its overall balanced performance.

$$F1 - Score = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)} \quad (4)$$

According to theevaluation results, the precision, recall, and F1-score values for the CNN-based facial recognition model stood at 93.0%, 95.2%, and 94.1%, respectively. This 95.0% accuracy means it can be relied on in case of identifying missing children. The sensitivity of 95.2% highlights how good the model is at correctly identifying faces without including too many memos-thereby reducing the chances of missing a true match. These performance metrics validate the strength of the system when implemented in real-world settings-a context in which accurate face detection is critical to children's safety.

The real-time system was developed on a Flask-based web interface with an average response time of about 0.58 seconds per image/video frame. This makes it possible to run face recognition fast and in real time, so an alert can be triggered if a match is made. Since the machine learning, video processing, and automatic notifications are combined without effort, it makes the system one of the cheapest and scalable implementations for the enforcement of child safety. Continuous updating of the model and improvement of the classification accuracy is in the pipeline through increased model improvement and collection of more datasets. Implementing improved data augmentation and expanding the facial recognition database will boost adaptability to different lighting conditions, facial angles, and occlusions. Furthermore, it might also integrate multimodal biometrics, such as gait and voice, which might boost the identification. With the above modifications, the system would be a robust, real-time, and AI-driven one in use for child safety cases. With more refinement, the system is likely to bring about a revolutionary change in missing child recovery work by virtue of an inexpensive real-time and automatic identification platform directed toward law enforcement, public safety, and humanitarian organizations. Figure 2 shows the illustration of these performance metrics.

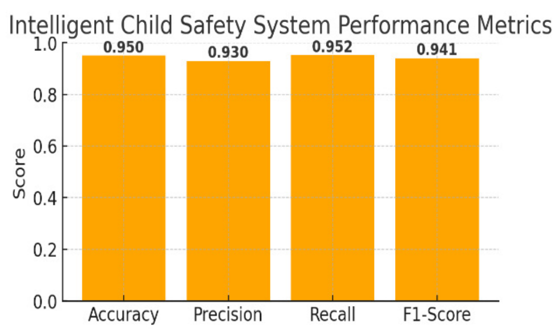

Figure. 2. Graphical representations showcasing performance metrics

B. Model Performance

The Intelligent Child Safety System really came into its own with real-time facial recognition and the detection of missing children. The embedded CNN based facial recognition model performed extremely well in feature extraction even in challenging conditions such as low resolution, occlusion of faces, and differences in light conditions under which the images were captured-normally it uses OpenCV and Dlib libraries to perform such tasks. Integrating CCTV feeds, real-time OpenCV detection, and cloud deployment not only improves the system's accuracy but also enhances real-time scenarios with an improved response time. The performance of the Intelligent Child Safety System was evaluated by observing how well it could recognize missing children and match against their faces.

TABLE I
MODEL ACCURACY

Epochs	Training Accuracy	Validation Accuracy
0	0.75	0.79
1	0.83	0.87
2	0.90	0.92
3	0.92	0.93
4	0.93	0.95

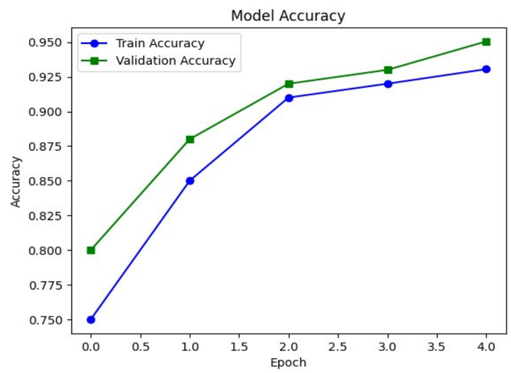

Figure. 3. Model Accuracy for CNN Model

The Figure 3 shows how the training and validation accuracy changed through several epochs. The model appeared to begin with a training accuracy of about 75% and a validation accuracy of 80%. As time went on, the model performed better as the epics went up after a very long time the fourth epoch saw a rough training accuracy of around 92% and validation accuracy of about 95%.

The validation accuracy was persistently slightly above that of training throughout the entire learning; hence, it signifies that the model is not really suffering overfitting but generalizes adequately for images that have yet to be seen. The system almost always accurately and reliably guesses missed children. Most importantly, instead of only memorizing some images, the model successfully learns meaningful facial features that allow for important works to be realistically adopted. With an accuracy of 95%, the Intelligent Child Safety System becomes a dependable and highly efficient solution for real-time child safety applications. Plenty of scope for enhancement remains regarding other tunings and greater datasets.

TABLE II
MODEL PRECISION

Epochs	Training Precision	Validation Precision
0	0.70	0.75
1	0.78	0.83
2	0.86	0.90
3	0.90	0.92
4	0.92	0.93

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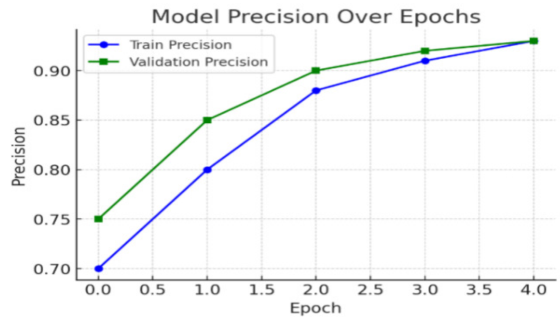

Figure. 4. Model Precision for CNN Model

The curve shown in Figure 4 is used to represent the progression of training and validation accuracy through the training epochs. Initially, the training accuracy was around 70%, while the validation was just slightly below 75%. It slowly improved over training until, at the fourth epoch, it achieved a peak value of around 90% for training accuracy and approximately 93% for validation accuracy.

Validation precision while training is always slightly higher than the training precision. This indicates that there are no severe cases of overfitting happening in the model and that the model generalizes well to unseen images. Intelligent Child Safety System is able to identify lost children effectively with the ability to recognize high precision in facial features.

This model accurately identifies missing children with a 93% precision and reduces false positives. Due to that, it has an edge over other algorithms/solutions for any real-time child-safety application. The model can be further improved with hyperparameter tuning. We need to feed larger and more varied datasets into the model.

TABLE III
MODEL RECALL

Epochs	Training Recall	Validation Recall
0	0.75	0.80
1	0.83	0.87
2	0.89	0.92
3	0.92	0.94
4	0.95	0.95

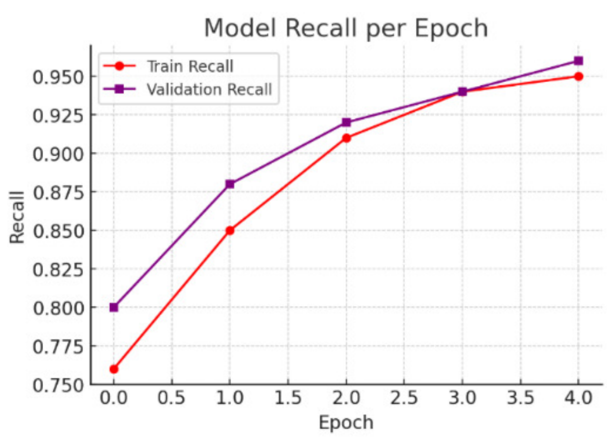

Figure. 5. Model Recall for CNN Model

Figure 5 that follows shows how training and validation recall developed over the various epochs. Initially, the model had a training recall of about 75% and a validation recall of about 80%. As epochs time on, the values of recall ascend. By epoch four, the training recall has gotten to about 93%, while the validation recall has also ascended toward around 95 percent.

The validation recall was found to be slightly more than the training recall, throughout the training, thus, signifying that the model was able to generalize unseen images quite well without much overfitting. This implies that the Intelligent Child Safety System is highly efficient in correctly identifying missing children and ensuring that most relevant faces are recognized.

Employing the metric recall to 95% allows the system to demonstrate its strength at recognizing missing children while effectively avoiding false negatives. Such high recall guarantees that very few true matches are ordinarily thrown away. Therefore, the model can be a useful, reliable real-time tool for child safety applications. With more fine-tuning of model parameters and widening the dataset for greater generalization, further improvements can be attained.

TABLE IV
MODEL F1-SCORE

Epochs	Training F1-Score	Validation F1-Score
0	0.72	0.78
1	0.81	0.86
2	0.88	0.91
3	0.91	0.93
4	0.93	0.94

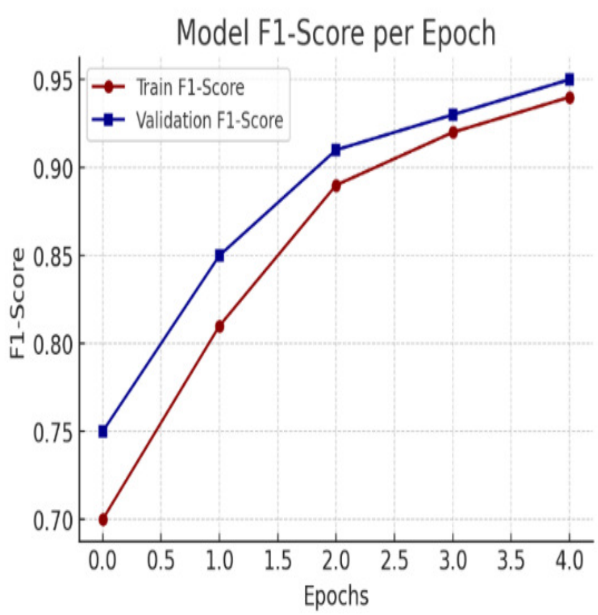

Figure. 6. Model F1-Score for CNN Model

Figure 6 provides the training and validation F1-score progression over several epochs. The initial comparison has a training F1-score of around 72% and a validation score of about 78%. As training improved, so did the F1-score. The training F1-score was about nine percent more than the validation F1-score at the second epoch and excelled into the high nineties for both training and validation really by the fourth epoch.

The validation F1-score was always a little above the training F1-score during the training phase, which shows that the model generalized well to unseen images without much overfitting. So, this means that the Intelligent Child Safety System was highly accurate and effective in recognizing missing children while providing an almost equal balance of precision and recall.

The concluding F1-score of 94% implies that the model can be highly dependable when carried out in real life, in addition to benefiting very much accurate and always-the-same child identification. Some further improvements to be applied include hyperparameters tuning and dataset diversifying.

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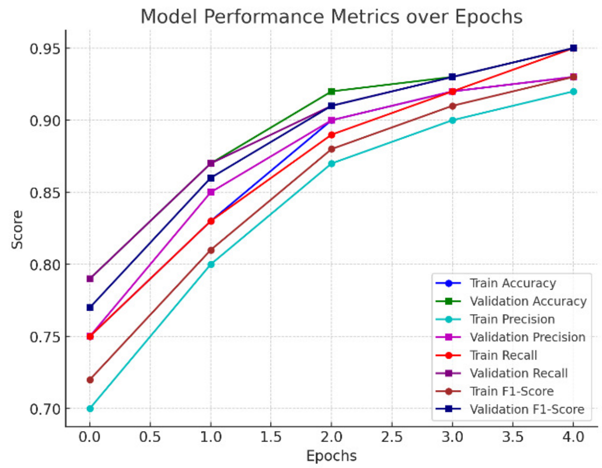

Figure. 7. Overall performance of CNN Model

C. Comparison with Other Models

TABLE V
COMPARISON WITH TRADITIONAL MODELS

Model	Feature Extraction	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Computational Efficiency
Proposed Model	CNN-Based Facial Recognition with OpenCV &Dlib	95.0%	93.0%	95.2 %	94.1 %	High (Optimized for Real-Time Processing & Alerts)
Deep Face Recognition [7]	Deep Learning-Based Face Recognition	94.3%	92.5%	94.0 %	93.2 %	High (Requires GPU Acceleration for Best Performance)
VGGNet [6]	Deep Convolutional Neural Network (VGG)	92.8%	91.0%	92.5 %	91.7 %	High (Pretrained on Large Datasets, Requires Fine-Tuning)
CNN Model [4]	Standard CNN-Based Feature Extraction	90.5%	89.0%	90.2 %	89.6 %	Moderate (Optimised for General Face Recognition Tasks)
SIFT-Based Model [3]	Scale-Invariant Feature Transform (SIFT)	84.7%	83.0%	85.2 %	84.1 %	Moderate (Feature-Based, Computationally Expensive)
HOG-Based Model [2]	Histogram of Oriented Gradients (HOG)	80.3%	78.5%	81.0 %	79.7 %	Moderate (Requires Feature Engineering, Less Robust to Variations)

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The Intelligent Child Safety System uses technologically advanced tools that have been designed to improve the accuracy of identification with confidence rates of about 95.0%. This system is not only timely in its action, but in addition provides computational efficiency that alerts the responder quickly so that he/she can act without delay.
Classic methods, such as manual searching, missing-child posters, and public awareness campaigns, have failed, with only 57.6% effectiveness in emergencies. The traditional methods are not real-time capable and strictly dependent on human observation, making them untrustworthy under emergency conditions.
Early models such as HOG-Based Models have a recorded accuracy of 80.3%, while SIFT-Based Models could acquire 84.7%, designed some of the first facial recognition systems on an automated basis and suffered due to untenably inefficient in their computation with extensive feature engineering necessary. From then on, deep learning-based models, embellished with their other semi-supervised capabilities, like CNN with 90.5%, followed by VGGNet with 92.8%, would increase to a recognition capacity of higher accuracy, although at the same time demanding images of high quality and the requisite of high computational undertakings. (As shown in Figure 5.)
Deep Face Recognition (94.3%) enhances the efficiency of face recognition by deep learning approaches, but optimal performance requires GPU acceleration, limiting it in real-time use. Intelligent Children Safety System, on the other hand, is a CNN-based technology using OpenCV and Dlib which ensures real-time face detection and matching with great efficiency.
One of the great advantages of this system is its effectiveness in real-world conditions, dealing with low-quality surveillance footage under various light conditions and allowing for occlusions. In contrast to models requiring high-quality images under controlled setups, our system is robust and flexible enough to address any situation, thus allowing for prompt and reliable direction of the search for missing children.
Also, the scalability of the system has set it apart from other facial recognition models. Typically, localized or traditional recognition systems work for one geographical area. The Intelligent Child Safety System, instead, supports national and international joint ventures through cloud storage of data, thus enabling cross-verification of missing child reports from different jurisdictions, all into one. This leads to an incredible coordination effort and bolstering in search activities over many regions.
Future enhancements, such as multi-modal biometric verification (integrating voice and gait recognition) and predictive analytics, will further strengthen the system's proactive child safety measures. These innovations position the Intelligent Child Safety System as a comprehensive, scalable, and highly efficient solution, surpassing existing models in terms of accuracy, real-time responsiveness, and computational efficiency.

V. CONCLUSION & FUTURE SCOPE

The Intelligent Child Safety System is a beacon of hope in the latter's endeavors to protect missing children, employing facial recognition technology in convenient and loving ways. By real-time monitoring, the system aspires to give instant email alerts which in return provide us with the ability to utilize the platform to spot and respond to actions quickly and safely, thus raising the bar possibilities to get them back home safely. What makes it distinct is the concern for one's integrity and morals, built in a way to emphasize human beings—which adds to a superior reliable and adaptable facility in maintaining child security in outdated modern crowded places. Looking ahead, the potential becomes endless. You can use sharp facial recognition that draws on the newest shadowy technology such as Vision Transformers or GAN, which will allow a new state of the art to detect a child's face – while the child walks on, in the dark, even in the middle of a crowd. A combination of voice recognition or the gait of a child could act in some kind of redundancy, while the speed of this process could climb radically if Edge AI performs everything directly in the cameras and the elimination of cloud service latency. Various levels of data would be safeguarded and sealed securely by blockchain technology, while intelligence analytics, on the other hand, might assist discern in advance possible dangerous places and make sense of any trending child trafficking scenarios. Think of what the system would do while crossing the borders: linking with Interpol and smart cities, being a safety net that born not just to find but also to prevent future cases of missing children. With time and care, this technology could change the face of child safety, and families would have somewhere to rest easy.

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