PORTAL FINDING FOR MISSING CHILDREN USING DEEP LEARNING ALGORITHMS

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ABSTRACT:

Every 30 seconds, a child goes missing in India and majority of them are girls and from poor socio-economic background. Referring to government figures accepting that only 55 percent of them are fortunate to reach their homes, the Supreme Court observed that nobody seems to care about missing children. This is the irony. Many of these missing children tragically find themselves being trafficked to an unknown and dangerous world which is sometimes thousands of miles away from home and end up as child labour, begging, inmates of a shelter home, or forced into trade. It is possible to ensure child protection and address the problem of missing children with active support of the civil society and fortunately there is face detection using dlib face detector and Resnet model. The present paper described the processes utilized by a parents will post they missing children in web application with manual and automatic location with resources that missing children reunite with their families. Choosing the foremost effective performing Resnet algorithm model for face recognition, Face and proper training of it finally ends up during a very deep learning model invariant to noise, contrast, image pose and also the age of the children and earlier methods in face recognition based missing child identification and child dead police case also identification using deep learning.

INTRODUCTION:

The main purpose of this design is to spot Missing Child Identification System using Deep Learning. In India a in numerous numbers of youngsters are reported missing when. Among the missing child cases an oversized chance of youngsters remains untraced. The general public can upload photos of suspicious child into a standard gate with milestones and reflections. The prints are automatically compared with the registered prints of the missing child from the depository. The Convolutional Neural Network (CNN), a largely effective deep literacy fashion for image grounded operations is espoused then for face recognition. The bracket performance achieved for child identification system is 99.41. It had been estimated on 43 Child cases. Children are the topmost asset of every nation. The longer term of any country depends upon the correct parenting of its children. India is that the alternate vibrant country within the world and youngsters represent a big chance of total population. But unfortunately, an outsized number of youngsters go missing when in India because of colorful reasons including hijacking, run-away children, traded children and lost children. The kids who missing could also be exploited and abused for colourful purposes. As per the National Crime Records Bureau (NCRB) report which was cited by the Ministry of Home Affairs (MHA) within the Parliament (LS Qno. 3928, 20-03-2018), further than one lakh children (in factual figures) were reported to possess gone missing till 2016, and of them remained untraced till the top of the time. Numerous NGOs claim that estimates of missing children are much advanced than reported

Numerous studies have focused on improving face recognition technologies across diverse environments and use cases, particularly emphasizing surveillance, real-time detection, and specialized domains. These advancements are crucial in addressing challenges in face recognition accuracy and efficiency, especially in complex, uncontrolled environments. Below is a review of significant contributions in this domain.

Chinese Face Dataset for Face Recognition in an Uncontrolled Classroom Environment (2023) addressed the challenge of face verification in uncontrolled environments by constructing a dataset (UCEC-Face) using real classroom surveillance videos. They observed that common models like Open Face and Arc Face struggled to perform well on this dataset, achieving only 69.7% accuracy. Their study highlighted that the lack of sufficient diversity in existing datasets for Asian faces in uncontrolled environments remains a barrier to reliable face verification, showcasing the importance of datasets tailored for real-world conditions [1].

Surveillance System for Real-Time High-Precision Recognition of Criminal Faces From Wild Videos (2023) proposed an advanced real-time surveillance system that focuses on identifying criminals through video footage using a deep learning-based face recognition method. Their system employs a down-sampled image strategy for faster detection and a face tracking ID unit to enhance accuracy by minimizing false predictions. With an accuracy of 0.900 and an F-1 score of 0.943, their approach demonstrates how real-time face recognition, combined with tracking and score-based validation, can be highly effective in real-world scenarios like criminal detection [2].

Real-Time Implementation of Face Recognition and Emotion Recognition in a Humanoid Robot Using a Convolutional Neural Network (2022) explored the implementation of face and emotion recognition in humanoid robots, combining these two aspects for real-time application. Using CNN architectures like Alex Net and VGG16, they found that VGG16 performed significantly better, achieving 100% accuracy for face recognition and 73% for emotion recognition. This work underlines the potential for integrating emotion and face recognition in robotics, which could have implications for detecting emotional states in humans during face recognition tasks [3].

NICU face: Robust Neonatal Face Detection in Complex NICU Scenes (2022) focused on the unique challenges of detecting neonatal faces in NICU environments, where traditional face detectors often fail due to complex factors such as medical equipment and lighting conditions. Their model, NICU face, was fine-tuned to detect neonatal faces in these difficult environments and showed substantial improvements in accuracy compared to existing detectors like MTCNN and Retina Face. The study emphasizes the necessity of creating specialized models for particular use cases, such as neonatal care, which shares similarities with challenges faced in detecting missing children in varied environments [4].

Adv Faces: Adversarial Face Synthesis (2021) introduced Adv Faces, a method for synthesizing adversarial face images designed to evade detection by state-of-the-art face recognition systems. Using generative adversarial networks (GANs), their model generated minimal, imperceptible perturbations that could deceive face matchers in obfuscation and impersonation attacks. This research highlights the vulnerability of current face recognition systems to adversarial attacks and underscores the need for secure face recognition solutions, particularly in sensitive applications such as child identification [5].

Collectively, these studies demonstrate significant progress in enhancing face recognition technologies under various conditions, from surveillance and robotics to medical environments. Each work contributes valuable insights into the challenges and solutions for improving accuracy, efficiency, and security in face recognition systems, which are essential for developing robust methods for identifying and reuniting missing children. These advances form the foundation for ongoing research into making face recognition more adaptable to real-world complexities.

EXISTING SYSTEM:

Deep Learning-Based Face Recognition

Models utilize artificial neural networks with multiple layers to automatically learn and represent facial features for identification and verification tasks. These models excel at capturing intricate patterns within facial images, enabling them to discern unique characteristics that define an individual's face. Through a process called feature extraction, the models transform raw image data into compact, high-dimensional embeddings that emphasize key facial attributes. Typically, Convolutional Neural Networks (CNNs) and HAAR Classifier are employed for their ability to learn hierarchical features from raw pixels. These models are trained on vast datasets containing labelled images of faces. During training, they adjust their internal parameters to minimize the difference between predicted identities and actual labels. Once trained, the models can compare new faces with the learned embeddings to recognize or verify individuals. Deep learning-based face recognition models have demonstrated remarkable accuracy, revolutionizing security systems, user authentication, and various applications reliant on facial identification.

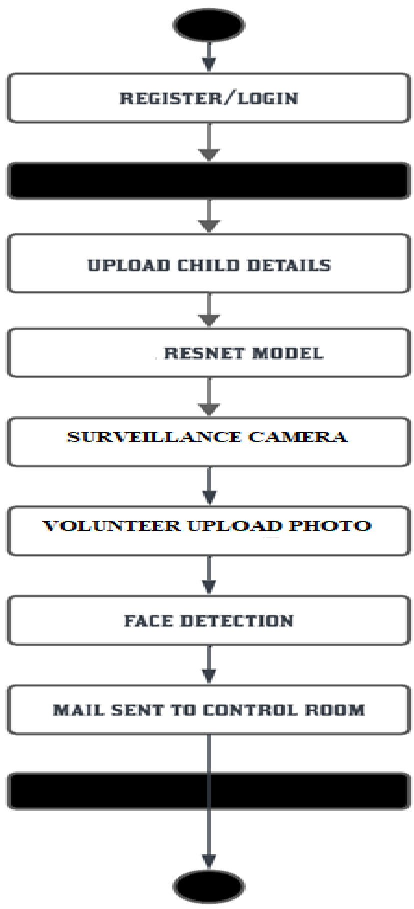
The main disadvantages in missing child identification system in existing system , daily nearby 100+ children are missing some child are found and a few child aren't found.

And there isn't any system available to spot the facial expressions of kid in a different environment like noises, lightning conditions with different facial attitudes and with different children.

PROPOSED SYSTEM:

The proposed system for a missing child identification combined with both the facial feature extraction concepts using in Open CV and matching concepts using Resnet model classifier algorithm in surveillance camera. This system utilizes face recognition for the missing child identification using surveillance camera and images are acquired using a camera to capture image frames. An image is then detected from the video feed using classifiers, which are used with the OpenCV library. Shape predictor 68 face landmarks is an dat file, which is trained to detect objects on still images or in live videos. Image detection commences whenever the Video Capture (0) method returns a true value thus the camera will be turned on. At this stage, the image is given a label that will be further used for training. The model we can use facial recognition whereby surveillance cameras are installed at convenient places to track people moving via the live video feed. This will be different from searching the whole nation for the missing child.

These projects can leverage advanced technology such as facial recognition systems and artificial intelligence algorithms to improve the accuracy of identifying missing children.
The data collected from surveillance cameras can be analysed to identify patterns and trends related to child abduction and missing children cases. This data can inform policy decisions and preventive measures.



MODULE DESCRIPTION:

This study has five modules for evaluating the bias during the training process

1. Upload details and admin verification

A crucial component of the system is the process through which parents upload their child's details in their time of distress. Parents are provided with a user-friendly platform where they can enter essential information such as the child's name, age, Aadhar number, and most importantly, a recent image of their missing child. Additionally, parents are required to submit a copy of the First Information Report (FIR) registered with law enforcement authorities, which documents the

details of the missing child's case. Once the parents have uploaded this vital information, and then verify the authenticity and accuracy of the FIR copy provided. This verification step is of utmost importance as it ensures the legitimacy of the reported case and safeguards against potential misuse of the system. If the FIR copy is confirmed to be valid and consistent with the data provided, the information is then securely moved into the database.

We will be training Long Short-Term Memory (LSTM) network using this generated sequential data in the Training Phase. The LSTM is made for picking up on patterns that arise in sequential data, which makes it a very useful tool to identify biases within the CNN models. The LSTM (Long Short Term Memory) network is trained and it has the ability to recognize correlation between structures of the networks (operations & parameters etc.) and its accuracies over epochs. The LSTM looks at the predictions, which they detect might simply arise from certain configurations of CNNs as being potentially biased. This step is important because it allows the LSTM network to calculate bias, which will then be used real-time when new models are being deployed. This turns the LSTM into an analytical heart of this system for a deeper insight on what may cause bias in neural networks.

2. Training the uploaded image using res net model

In the Resnet algorithm used for face recognition, the training process involves a critical step where a set of facial images is used to create a model that can later be used for recognition. These images serve as the foundation upon which the Resnet algorithm learns to recognize faces. During training, a collection of face images is provided as input to the algorithm. These images typically represent the individuals whose faces the system needs to recognize. Each facial image undergoes preprocessing steps, which may include resizing, grayscale conversion, and normalization to ensure consistent and comparable features. The core concept behind model is to extract texture information from the facial images. To achieve this, the algorithm partitions each face image into local neighbourhoods, and within each neighbourhood, it calculates D lib face recognition res net model.

Model represents texture patterns by encoding the relationship between a pixel and its neighbouring pixels. The algorithm processes through the entire set of training images, it accumulates knowledge about the distinctive texture patterns present in each person's face. This knowledge is stored in the form of histograms associated with each individual.

3. Shape predictor 68 face landmarks classifier to detect face

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4. Surveillance using web camera

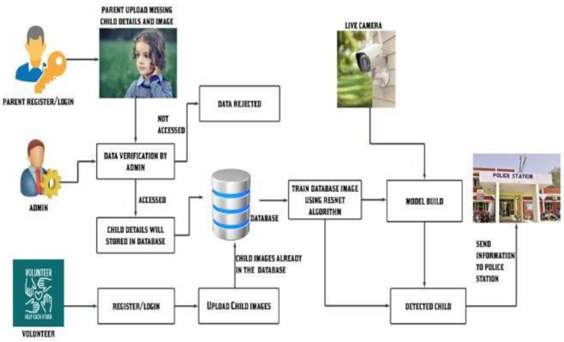
Web cameras are strategically placed in key locations across communities, including streets, parks, schools, and public transport hubs. Additionally, individuals can voluntarily contribute by allowing access to their home security cameras. Advanced facial recognition technology is employed to scan the incoming video streams for potential matches with the uploaded images of missing children. This technology can identify and flag any instances where a missing child is detected. The system promptly initiates a seamless process

where the relevant child details, including the child's name, age, and any other identifying information, are securely transmitted to the nearest police station or law enforcement authorities. This data transfer occurs in real-time, facilitating an immediate response from the authorities.

5. Volunteer module

In this system, individuals can voluntarily upload images of missing children, which are then verified against a comprehensive database using advanced facial recognition technology powered by the Res Net algorithm. When a volunteer submits an image, administrators can quickly check it against the database to identify potential matches. If a match is detected, the system flags the instance and initiates a secure, real-time data transfer process. Relevant information, including the child’s name, age, and any identifying details, is promptly transmitted to the nearest police station or law enforcement agency to facilitate an immediate response. Simultaneously, notifications are sent to the child’s parents or guardians, ensuring they remain informed of any developments. This solution aims to enhance the efficiency and speed of responses in missing child cases, providing timely assistance and fostering community engagement in safety efforts.

ARCHITECTURE DIAGRAM:



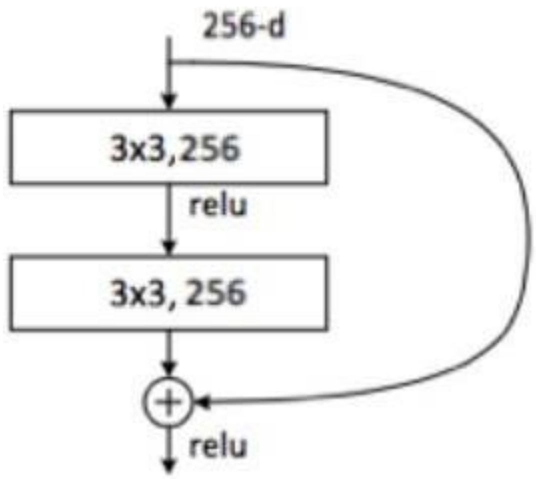
Proposed algorithm:

1. Convolutional Neural Networks (CNN) Algorithm

Convolutional Neural Networks (CNN) are highly effective for image classification due to their ability to automatically detect patterns and features in +images through a series of convolutional operations. In CNN, filters slide over the input image, performing convolution operations to produce feature maps that highlight important characteristics, such as edges and textures. Pooling layers, typically max-pooling, reduce the spatial dimensions of the feature maps, preserving essential information while lowering computational costs. CNN's hierarchical structure enables the model to learn complex features at deeper layers. As a result, CNN is a preferred choice for tasks such as facial recognition, medical imaging, and object detection, where spatial data relationships are crucial.

2. Residual Networks (ResNet) Algorithm

Residual Networks (ResNet) are designed to overcome the challenges of training very deep neural networks, particularly the problem of vanishing gradients. ResNet introduces skip connections, where the output from one layer is directly passed to a deeper layer, bypassing intermediate layers. This innovation allows the network to learn residual mappings, making it easier to train deeper models without degradation in performance. As more layers are added, ResNet improves accuracy by ensuring that the model continues to learn relevant features. This architecture has enabled the development of networks with hundreds or even thousands of layers, making ResNet ideal for complex tasks such as image recognition and classification.



Output:

The output of the proposed system is highly efficient, secure, and operates in real-time to aid in locating missing children using advanced facial recognition technology, along with a robust data verification process and community participation.

Upon a parent or guardian's submission of their missing child's details, including the child's name, age, Aadhar number, recent photograph, and First Information Report (FIR), the system confirms the successful upload of this information. The FIR undergoes an administrative verification process to ensure the authenticity and validity of the case. Once verified, the data is securely stored in the system's database. This ensures that all reported

cases are legitimate and that the system is not misused. Parents are notified of successful registration and verification, enabling the system to move to the next stage of facial recognition.

The child's image, once uploaded, is processed by the ResNet model for facial recognition training. The system analyses the facial features and texture patterns, building a recognition model specific to the child. The output of this training process is a facial model that is ready to be matched against incoming surveillance feeds or uploaded images.

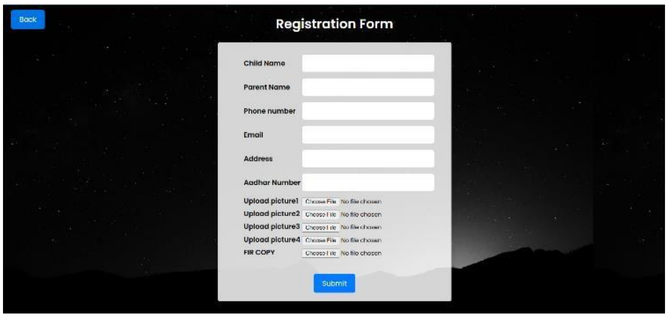
Simultaneously, the 68 Face Landmarks Classifier detects key points on the child's face, creating a precise facial map. This output aids in the accurate detection of the child in both static images and video feeds, allowing for robust face recognition even in challenging environments.

When a match is detected, either from live surveillance footage captured by strategically placed cameras or from volunteer-uploaded images, the system generates a real-time alert. This alert includes key details such as the child's name, age, and location, which are immediately transmitted to local law enforcement agencies. Parents or guardians also receive instant notifications, ensuring they are kept informed of the child's potential whereabouts. The system's secure, real-time data transfer enables swift action from the authorities.

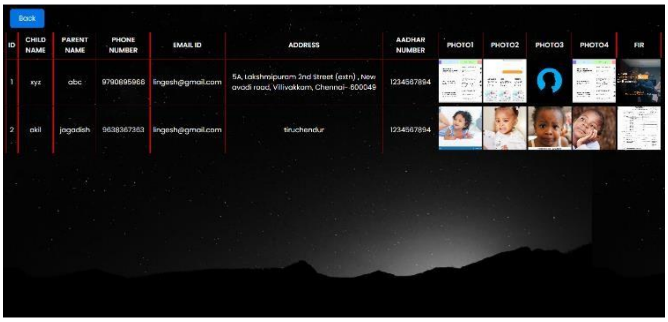
For volunteers, the system compares the submitted image against the database. If a match is identified, the system promptly flags it, triggering notifications to administrators, law enforcement, and the child's family. This process accelerates the identification and reconnection process for missing children. All activities, including data submissions, face matches, alerts, and notifications, are securely logged, ensuring the transparency and security of the system.

The system's combined modules work together to produce accurate, secure, and timely outputs, helping streamline efforts to reunite missing children with their families efficiently.

Output of web portal for finding missing child



Upload Rescuer and Parent input details



Parent and rescuer data stored

This image shows the front end of our Animal species classification site after providing input from the user.

CONCLUSION

The aim of this project was to develop a facial recognition system for finding missing child. All the objectives have been met thus determining the efficiency and accuracy of the system. The accuracy of the system was based on the face recognition rate and the efficiency of the system was determined by the computational time. The researcher developed the system using the OpenCV and python that helped him to build the crucial modules thus face detection and recognition. The system was tested and the results produced in the previous chapter shows that it is a good idea to introduce the system because it has a remarkable facial recognition rate and computational time. The system is convenient for police, Government and public by speeding up the process of searching the children's.

FUTURE WORK:

For future enhancement, this facial recognition system can be expanded and optimized in several ways to increase its impact and effectiveness in locating missing children. Firstly, integrating deep learning models such as Res Net or more advanced architectures could further improve recognition accuracy, especially when dealing with variations in lighting, aging effects, or partial obstructions. Additionally, expanding the database to include a more extensive collection of children's images and using data augmentation techniques could enhance the model's robustness and adaptability across diverse environments. To broaden accessibility, the system could be developed as a cloud-based application, enabling seamless access by authorized personnel from multiple locations, including police stations, community centers, and mobile devices. In terms of security, incorporating advanced encryption methods and privacy controls would help protect sensitive data, ensuring that images and information are accessed only by authorized users.

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