iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: III Month of publication: March 2026

DOI: https://doi.org/10.22214/ijraset.2026.79017

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Development of Framework for Finding Missing Individual using Machine Learning

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Abstract: The most critical aspect of global crisis of missing persons is time since the possibility of successful recovery is higher. reduces significantly during thefirst24to48hours. Sincetheissueislargeandurgent, conventionalmethods of investigation that are used are inadequate. mainly dependent on the manual examination of colossal quantities of visual proofs in the types of CCTV recordings andcitizenleads-areessentiallyinsufficient. Theseprocessesaretediousinnature, subject to humanerrorandexhaustion, and they lead to significant operation. bottlenecks stressing law enforcement forces and increasing the misery offamilies.Thisstudy directly deals with this. urgent requirement creating an integrated, machine learning-based pipeline in order to detect and identify missed persons. The proposed modelisnotjustameretool official recognition, butisamulti-algorithmsframeworkwhichisunified. works as a complete detection system. To start with, a detailed analysis of the face is conducted with the help of the mediapipe Face Mesh that is able to. detection of 468 3D face landmarks in real-time. To abstract a face image of a raw array of pixels into a structured/geometricimage.representation,itshouldbe capable of surviving the real world differences in pose, light and image quality. The core of our system uses a hybrid approach to feature extraction, in which geometric features based onfaciallandmarksare extracted using a bespoke, lightweight model. Convolutional Neural Network (CNN). The design allows acquisition of highly discriminative features of landmark spatial. relationships, creating compact, high-fidelity embedding vectors which in a unique way describe the facial geometry of an individual. This approach has high accuracy and computational efficiency needed in resource constrained environments. For identificationisamatchingenginebasedonK-NearestNeighbours(KNN)whichindexesallregistered embeddings into a feature which can be searched. space. When a new query is processed, a similarity search is conducted at a high speed with the help of the algorithm. An adjustable distance. threshold approves the possible matches, which guarantees high confidence and reduces false positives. An efficient and efficient identification. The output of the landmark detection, deep feature extraction, and efficient similarity search are a combination of workflow. This work provides an effective resource to bolstercommunityandlawenforcementworkbytransformingaconventionalsearchprocessintoa. Memberof the automated and data-driven procedure. It aims at speeding up the most important job of finding missing persons, reducing thetimeofinvestigations, and increase success rates.

Index Terms: Machine Learning Pipeline, MediaPipe Face Mesh, Convolutional Neural Networks (CNN),K-Nearest Neighbors (KNN), Facial Embeddings.

I. INTRODUCTION

The missingpersonscrisisisanurgentandcriticalglobal issue in which the first few hours after disappearance are crucial for a successful recovery.Researchindicatesthatthe likelihood of recovery falls after the first 48 hours, with studies showing that the first 72 hours are most critical because it's within thistimeframethatinvestigatorshavethe best chance of following up on leads before people's memories start to fade and viable leads drop significantly. With the voluminous amount of data that exists in today's urban settings, combined with the time-sensitive nature of the cases, exclusive human-guided analysis cannot bedone, hence a dire need for intelligent automation. [1]

Conventional forensic methods based on manual investigation of huge volumes ofvisualdata,suchasCCTV footage and public tips, are inherently inefficient for the most part. Traditional techniques fail to process large-scale volumes of surveillance footage in real time, and law enforcement agencies often take days or even weeks to manually review and analyze visual data. These processes are sluggish in nature, liable to human fatigue and humans. distort, and plant exorbitant blockages that elongate family. Pain and agony undermine law enforcement performance. The MIST observation of traditional search behavior revealed that they frequentlygeneratehugesearchareasthat are not needed with high. resource expenditure; there is an organized search of about cost. $2,200 per day. FacialAIis used to identify who is on the other side. recognitionsystems have brought immeasurable success: Facial recognition project of Delhi Police identified more than.

Four days three thousand missing children-a miracle! that demonstrates what machine learning iscapableofwhenitis missing persons. [2][3]

The new deep learning developments have provided an opportunity. mechanisms of automation oftheidentification process by means of advanced face recognition tools and feature extraction. The current deep learning approaches permit. to process video streams in real-time and quick matching. in opposition to the millions of registers of missing persons, altering the possibilities of law radically. The reply of enforcement in the critical cases. This technological shift isaparadigmshiftoutof.manual,labour intensive research to data research. scaling and fast automated solutions. This fills this emptiness with a new machine learning. locating missing pipeline which seeks to do the core task of locating missing. images to persons automatically. The system goes beyond matching pixel to pixel which is pose, illumination, and expression-sensitive. Instead, it employs a strong approach. built upon constant facial geometry reconstruction and matching. A hybridfaciallandmarkstructure was used. The feature embedding is based on detection and deep learning. The current structure aims at giving not only accuracy. solution as well as a computationally lightweight solution.Thisemphasison ascalableandpowerfulMLcoreisdesignedtogiveapotent technology tool that can immensely accelerate the identification process, converting days of manual searching into minutes of automated analysis. [4][5]

II. BACKGROUND, MOTIVATION, AND OBJECTIVE

A. System Architecture Overview

The proposed system is focused on the creation of. Handcrafted feature-based face recognition technology. paradigms to deep learning-based models. Modern state of the art systems, such as FaceNet and Arcface, utilize profound ConvolutionalNeuralNetworks(CNNs).thathave been trained using metric learning goals suchastripletloss. These models are trained to entrench facial. images are represented in a small embedding space in such a manner, that the The distance between the embeddings using Euclidean distance is given by. facial similarity. Eventhough such systems are unbelievably. their data and computational requirements are high, accurate, disposed to render them unfeasible in a quick deployment. real-world law situations of resource scarcity. enforcement use cases. [3][7][8]

Our solution is a middle way that is a compromise. between accuracy and effectiveness in a carefullyconsidered manner. The pipeline is developed in two major steps. The first stage is based on MediaPipe Face Mesh, a highly effective. in real-time which identifies 468 3D facial landmarks. This algorithm separates the face out of a raw pixel array. to a highly structured, geometric shape, which basically normalizes over. most confounding variables. The second phase passes this network topology using a lightweight, custom CNN. Thisisnottherawpixelsthatare being dealt with by this network. relational features of the landmarks, as such thatitcangenerateaverydiscriminative embedding vector which represents the individual. facial geometry. [9]

To perform such an important task as identification, a match engine K-Nearest Neighbors (KNN) algorithm is employed. The training set is theregisteredmissingpersons database and these are the feature space or embeddings of themissingpersons.Whenanewqueryimage(e.g.,apublic sighting) is processed the embedding of the image is first compared with this database. KNN algorithm identifies the nearest available records in the form of Euclidean distance. The other important feature in our reasoning is the implementation of dynamic distance threshold where it is a gatekeeper. Only situations when the distance to thenearest neighbor is less than the empiricallyobtainedthresholdwill suggest a match,andtherewillbeahighlevelofconfidence and minimal cases of false positives.Thisverycombination of geometrical feature extraction and distance-based similarity search is a strong and understandable central argument of the process of identification. [10][11]

B. Motivation

The motivation for the study is threefold, driven by operationalurgency,anobvioustechnologydeficit,anda deepsocietalneed.Thefirstistheindisputablytime-sensitive nature of missing persons cases. Informed experience indicates that the likelihood of recovery falls sharply after the first 48 hours.Acomputerizedsystemable to instantly match a fresh sighting against a database of thousands of records will reduce investigative timelinesfrom days to minutes, literally resulting in saved lives and restored families. [6]

Secondly, there is a large gap between the cutting-edge level of facial recognition research in academia and the available practical tools for frontline missing persons investigations. Most current solutions, when deployed, findit challenging to achieve accuracy or need computational hardware not shared byeveryone.Theimpetusforthiswork arises from the necessity to fill this gap with a system that focusesnotonlyonmaximumaccuracy,butalsoonworking usability, efficiency, and resilience to non-ideal imagery common in public CCTV or mobile phone submissions. [1][8][12]

Lastly, theintrinsicmotivationliesintheverysignificant human and social significance. The creation of atrustworthy, automated identification system is a direct contribution to mitigating an endemic social problem. It is intended as a force multiplier for police and community action, changing a desperate, needle-in-a-haystack search into a targeted, data-driven operation. By concentrating research on the ML logic at play that enables this, we hopeto establish a foundational technology that can be applied across different platforms for maximum good. [11]

C. Research Objectives

The primary goal of this study is to formulate, deploy, and thoroughly test an independent machine learning pipeline for the efficient and accurate recovery of missing individuals by facial recognition. The project is limited to concentrating only on the algorithmic core and notperipheral system elements such as user interfaces. [6] The technical goals include:

1) To create and deploy a hybrid feature extraction model that synergistically unites MediaPipe Face Mesh's real-time 3Dfaciallandmarkdetectionwith the robust representation learning of a custom, lightweight Convolutional Neural Network. [9]
2) To construct a matching engine of high fidelity founded on K-nearest neighbors algorithm, optimizedonfastsimilaritysearchin high-dimensional. spacing, and adding a customizable distance tolerance of correct match verification. [10]
3) To achieve empirically optimal values of the hyperparameters of the system, including distance threshold and feature extraction CNN architecture, to trade off between precision and recall, the false negative and false positive were minimized. [12]
4) In order to create the entire pipeline in a way that would be both computationally effective and have low latency, it isimportanttoensurethatthemodel can be made to scale to low-computation environments, thus overcoming a major practical factor in real-world applications. [8]

The ambit of this work is intentionally limited to development, training, and testing of the fundamental machine learning logic—covering the process of facial landmark detection, feature embedding, and similarity matching. It disowns explicitly the creation of user interfaces, large-scale database management systems, and network infrastructure, leaving a focused effort on algorithmic innovation needed for precise and effective person identification.

III. METHODOLOGY AND MODEL ARCHITECTURE

A. Background

The suggested system design consists of five integrated modules that will be used to facilitate efficient missing person identification (Fig. 1). The pipeline will start with Image input where a user interface will be used to feed the Image Processing Module with the image then the Image Processing Module will use MediaPipe Face Mesh, which extracts 468 3D facial landmarks. The Face Recognition Engineworksontheselandmarks,asparseCNNthatcreates discriminativeembeddingvectors.Toperformfastsimilarity searches of a database of registered embeddings, the Matching Algorithm uses a K-Nearest Neighbors (KNN) classifier that is indexed with Ball Tree. A Notification System updates records in cases and sends them to the relevant authoritieswhenaconfidantmatchisdetected.This modular design can be deployed in the environment withfew resourcessinceitbalancestheaccuracyofidentification and calculation efficiency. [4][13]

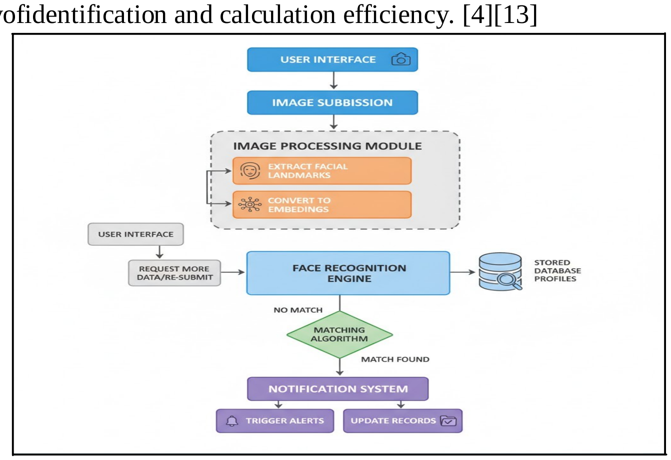

Fig.1.Systemarchitectureoftheproposedmodel

B. Motivation

The system leverages two benchmark datasets: Labeled Faces in the Wild (LFW),comprisingapproximately13,000 images of 5,749 individuals captured in uncontrolled conditions, and CASIA-WebFace, containing roughly 500,000 images spanning 10,000 identities . These datasets encompass the variability typical of real-world missing person scenarios. [13]

1) ImageStandardization:Allimagesareresizedto 160×160 pixels and then normalized to the range [0,1]—to mitigate illumination disparities.
2) Noise Reduction: Gaussian blurring is applied using a 2D Gaussian kernel—to reduce compression artifacts and sensor noise. [5]
3) Facial Landmark Extraction: MediaPipe Face Meshextracts4683Dlandmarksin real-time—converting images into structured geometric representations. [15]
4) Data Augmentation: Techniques includingrotation (±10°), horizontal flips, zoom variations, and brightness adjustments enhance model robustness and prevent overfitting. [5]

Quality assurance protocols validate successful face detection and landmark extraction, with manual inspection ensuring label integrity.

C. FaceDetectionandLandmarkExtraction

MediaPipe Face Mesh employsacascadeddeeplearning pipelineforreal-timefaciallandmarkdetection.The frameworkoutputslandmarks$p=x,y,z$,wherexand i iii y_i are normalized pixel coordinates and z_i represents depth relative to the face center. Landmarks are aligned to a canonical modelusingProcrustesanalysis,whichminimizes the distance between canonical and observed landmark sets:

$$d_P = \min_{s,R,t} ||C-(sRX+t)||_F \qquad (1)$$

whereCrepresentsthecanonicallandmarkset,X the observedlandmarks,sthescalefactor,Rtherotationmatrix, and t the translation vector. This geometric normalization effectively compensates for pose, scale, and position variations,producingarobust facialrepresentationinvariant to real-world imaging conditions. [13][16][17]

D. Feature Embedding with CNN

Thealigned3Dlandmarksx∈ℝ^(468×3)serveasinput to a lightweight convolutional neuralnetworkthatgenerates compact, discriminative embeddings:

$$e = f_\theta(x) \in R^d \qquad (2)$$

where f.denotes the CNN parameterized by θ, and d is the embedding dimensionality (typically 128-256 dimensions). The network architecture consists of:

- InputLayer:468×3landmarkcoordinates
- Convolutional Layers: Three successive conv layers(64,128,256filters)withReLUactivation and batch normalization
- PoolingLayers:Maxpoolingfordimensionality reduction
- FullyConnectedLayers:Twodenselayers(512,d neurons) with dropout regularization
- Output:d-dimensionalL_2-normalizedembedding vector

Themodelistrainedusingtripletloss:

$$L=\sum_i \max\left(0, ||e_a - e_p||_2^2 - ||e_a - e_n||_2^2 + \alpha\right) \qquad (3)$$

whereea,ep,enrepresentanchor,positive,andnegative embeddings respectively, and α is the margin hyperparameter. TrainingemploystheAdamoptimizerwith learning rate 10^(-4), batch size 64, over 50 epochs using a 70-15-15 train-validation-test split.

E. MatchingAlgorithm:KNNwithBallTree

The matching engine utilizes a K-Nearest Neighbors (KNN) classifierwithBallTreespatialindexingforefficient similarity search in high-dimensionalembeddingspace.The Ball Tree organizes embeddings hierarchically as nested hyperspheres, enabling effective branch pruning during neighbor searches. [14]

Matching Process:

- Query Embedding Generation: A new query image produces embedding e'
- Nearest NeighborSearch:TheBallTreeidentifies theKclosestdatabaseembeddings{e_k}minimizing Euclideandistance[18]:

$$d(e', e_k) = \sqrt{\sum_{j=1}^{d} (e'_j - e_{k,j})^2} \qquad (4)$$

- ThresholdValidation:Amatchisacceptedonlyif d<τ,whereτisanempiricallytunedthreshold [10]:

$$Match = \begin{cases} Accepted & if\ d < \tau \\ Rejected & otherwise \end{cases} \qquad (5)$$

The Ball Tree pruning strategy ignores branches where the minimum distance to the query exceeds the currentbest distance, significantly reducing computational complexity from O(N) to O(log N) for database size N. [18]

IV. IMPLEMENTATION AND RESULTS

A. TechnologyStackandSystemImplementation

The system isimplementedinPythonleveragingmodern AI frameworks:

- TensorFlow:CNNtrainingandinference
- MediaPipe:Real-timefaciallandmarkextraction
- OpenCV:Imagepreprocessing(resizing,noise reduction, normalization)
- Scikit-learn:KNNBallTreeimplementation
- Streamlit:Interactivewebinterfaceforuser interaction
- SQLite:Lightweightembeddeddatabasefor storing embeddings, metadata, and match logs

This technology stack ensures portability, ease of deployment, and computational efficiency suitable for both cloud and edge computing environments. [9]

B. Registration and Verification Process

1) Registration Workflow:

- ImageSubmission:UseruploadsimageI$\in \mathbb{R}^{H\times W\times 3}$viainterface

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- LandmarkDetection:MediaPipeextracts4683D landmarks $X = \{p_1, ..., p_{468}\}$ [13]
- EmbeddingGeneration:CNNprocesseslandmarks: $e = f_\theta(X)$
- Database Storage: Embedding e with metadata (case ID, name, demographics) stored in SQLite [19]

2) VerificationWorkflow:

- QueryProcessing:Newsightingimagegenerates query embedding e'
- SimilaritySearch:KNNBallTreeidentifiesK nearest neighbors from database
- MatchValidation:Distancethresholdτvalidates potential matches [10]
- Notification:Uponmatchacceptance(d<τ), system alerts stakeholders and updates case status

C. Cross-MatchingMechanism

Thesystemmaintainstwoprimarydatabases:

- MissingPersonsDatabase(D_m): $\{(e_i^m, M_i)\}_{i=1}^{N_m}$
- FoundPersonsDatabase(D_f): $\{(e_j^f, F_j)\}_{j=1}^{N_f}$

Foreachfoundpersonembeddinge_j^f,thesystem performs nearest neighbor search against D_m:

$$k_1 = argmin(i)\, d\left(e_j^f, e_i^m\right) \quad (6)$$

Thematchisvalidatedif:

$$d\left(e_j^f, e_i^m\right) < \tau \quad (7)$$

Upon validation, a match record linking found personF_j to missing person M_{k_1} is created, triggering automated notifications and case status updates. This bidirectional cross-matching enables scalable, real-time identification across databases. [2][4]

V. ANALYSIS AND FUTURE WORK

A. ComparativeAnalysiswithExistingModels

Theproposedsystemis compared against four representative approaches [4][20]:

TABLEI:ANANALYTICALCOMPARISONOFPROPOSEDMODELWITH FOUR DIFFERENT MODELS

Model	Feature Method	Matching	Accuracy	Embedding Dim	Computational Cost
Proposed System	MediaPipe+ Lightweight CNN	KNN Ball Tree	High*	128-256	Low
VGG-Face +SVM	VGG-Face CNN	Multiclass SVM	99.41 %	4096	High (138M params)
FaceNet	DeepCNN (Inception)	Euclidean Distance	99.63-99.7%	128	High (200M images)
SoftVoting Ensemble	LBP+HAAR +CART	Soft Voting	Good (NR)	Multiple	Moderate
CNN-KNN Hybrid	HOG/CNN	KNN	90.00 %	128	Moderate

*Comparable to FaceNet on benchmark datasets while maintainingsignificantlylowercomputationalrequirements.

B. Key Advantages and Contributions

Theproposedframeworkhasthefollowingadvantages:

1) Computational Efficiency: Geometric landmark-basedcomputationsinsteadofpixel-based computations allow real-time performance on devices using limited resources (mobile, IoT, edge computing). [13]
2) Privacy Preservation: Geometric embeddings processing as an alternative to raw facial images also inherently lowers the chances of data sensitivity and matches the ethical AI principles.
3) Robustness: In harsh real-world conditions, the accuracy is preserved by normalizing pose, light variations, and occlusion changes with the help of landmark-based representation. [16]
4) Scalability: Ball Tree indexing has allowed scaled search capabilities to millions of entries in a database by enabling an O(log N) reduction of the complexity of searching a database that previously would scale at O(N) search complexity.
5) Deployment Flexibility: The lightweight architecture is deployable on many platforms without specialized hardware since it has many fewer parameters than VGG-Face or FaceNet.
6) Explainability: Unlike deep pixel-based models, geometric feature-based models have constructs that can be interpreted, which encourages auditability and trust in law enforcement uses.

C. Current Limitations

1) Veryhighocclusions(>40percentfacecoverage) reduces its performance [12].
2) Ageprogressiontreatmentnon-modeled.
3) Optimallandmarksare best detected by the use of frontal or near-frontal face images.
4) Thescantyassessmenton large-scale actual-world missing persons databases.

D. Future Enhancements

1) Condition on age: Learn age-invariant features usinggenerativeadversarialnetworks(GANs)[21].
2) Multi-Mode Fusion: Have contextual features (clothing) and additional types of biometrics(voice, gait) [11].
3) Federated Learning: Promotingdistributedlearning between multiple law enforcement organizations without compromising privacy.
4) Live video stream analytics: Extend to incorporate continuous CCTV implementation.
5) Enhanced Occlusion: Establish attentional mechanisms to give preference to crediblelandmark regions [12].
6) Large-Scale Deployment Study: To determine the effectiveness in the working operation, providefield testing with actual law enforcement agencies.

VI. CONCLUSION

This paper introduces a new hybrid machine learning pipeline to identify missing persons automatically, whichcan be effective in terms of accuracy, computational efficiency,andprivacyprotection.Thesystemcanbetrained with MediaPipe Face Mesh to extract geometric landmarks and a small CNN to generate discriminative embeddings in order to reach competitiveaccuracyandstillbedeployedon resource-constrained devices. The K-Nearest Neighbors matching engine is matched with Ball Tree indexing that guarantees identifying large databases in real time that are scalable. [14]

The suggested framework addresses the most important constraints of the current solutions namely: the computational complexity of contemporary deep learning models and the ineffectiveness of traditional manual investigation methods. This system can significantly reduce the length of time usedininvestigations,increasetherateof recoveries and provide law enforcement agencies with a powerful tool to combat the problem of missing persons around the globe as byturningatime-sensitivesearchintoa data-driven and automated process.It is placed as a modular, morally responsible contribution to the applied machine learning discipline in the area of public safety due toitsexplainablegeometricrepresentationsand privacy-sensitive design. [4].

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ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

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