International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Deep Learning-Based Approach for Identification and Recognition of Criminals

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Submitted: 28/04/2023 **Revised**: 25/06/2023 **Accepted**: 04/07/2023

Abstract: Face sketch recognition is one of the most researched issues in forensic science. Automatically retrieving suspect mug-shot images, police record can facilitate them swiftly tapered down and eliminate prospective suspects, but in most circumstances, a suspect's photographic image is not available. Sketching from the memories of an eyewitness or a victim is frequently the best substitute. In general, this procedure is slow and ineffective, as it does not allow for the identification and arrest of the appropriate culprit. As a result, a more powerful algorithm for even partial face sketch recognition is frequently beneficial. Many solutions have been offered in this scenario, particularly the techniques used in face recognition systems, which are regarded among the best and most effective. Our project uses deep learning and cloud infrastructure to allow users to create composite face sketches of suspects without the assistance of forensic artists using the application's drag and drop feature, and to automatically match the drawn composite face sketch with the police database much faster and more efficiently.

Keywords: *Forensic Face sketch, Deep Learning, ANN, Criminals, Attack*

1. Introduction

Crime is a very crucial topic that affects the quality of life in society. Depending on the sort of town and the most likely crimes based on data and statistical analysis. There has been ongoing research in this area all around the world. Data gathering, classification, pattern recognition, prediction, and demonstration are frequent components of machine-based crime analysis. Correlation analysis, segmentation and prediction, cluster analysis, and external analysis are examples of traditional data mining techniques that uncover patterns in structured data, whereas newer techniques find patterns in both formal and informal data. The creation of a prediction model that can correctly predict criminals is the major goal of this endeavour.

Based on eyewitness descriptions, face sketches created can be used for rapid identification and prosecution of criminals. On the other hand, the current highly developed technology civilization, hand-drawn sketches used for matching and identification with pre-existing databases or real-time databases that have not proven to be as efficient or time-saving. When it comes to using hand-drawn face sketches with the latest crime detection and identification technology, forensic science have shown that they are still limited and time-consuming. Face sketches created based on eyewitness descriptions can be used to quickly identify criminals and prosecute them. However, in today's technologically advanced society, hand-drawn sketches for comparison and identification with pre-existing databases or real-time databases are not found to be as efficient or time-saving. The application's drag-and-drop functionality allows permits clients to make composite suspect's facial sketches without the assistance of forensic researchers. Using deep learning [1]–[3] and cloud computing [4-5],[30-33] the composite facial sketch that is created is then automatically matched to the police database.

The objective of the work is described as

- Making an accurate and simple composite sketch of the culprit.
- Accuracy with the high positive probability of detecting the criminal.
- Utilizing an effective locking system for data protection.

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- Data backup is feasible in the event of node failure.
- The entire prediction ensures backward compatibility.

The deliverables of the work are as follows

- An application that allows users to submit sketches directly or create them using drag-and-drop functionality. The drawing is then compared to databases using feature extraction to show similarities.
- The application features a two-way locking system, which makes it incredibly secure.
- Criminals may be quickly detected with this application, which also benefits the police force by making their work easier and faster.
- The application's accuracy hovers around 90%.

2. Related Works

A critically and concisely analyzed 20 standard research and literature papers related to Face sketch construction using various techniques is done. We carefully examined the suggested technique and identified its shortcomings in the selected research publications. Using a pre-defined set of facial features as tools to scale and arrange a sketch in accordance with requirements is referred to as face sketch creation. The automatic recognition of a person from a collection of facial images using a face sketch is known as face sketch recognition. A few techniques used for the construction and recognition of face sketches are the transfer learning method and 3D morphable model, a traditional feature-based system, using the AdaBoost algorithm, Self-Organizing Map (SOM) Neural Network with Two-Dimensional Discrete Cosine Transform (2D-DCT), A novel perception adaptive network (PANet), A pre-trained model called FaceNet (FN), Python-based applications for classification, Local Radon Binary Pattern(LRBP), a face, Inter-modality face recognition approach using coupled Information-theoretic projection tree.

In [6], the subtleties of how wrongdoing is carried out change contingent upon the kind of local area. Wrong gauging is a form of policing that utilizes information and factual investigation to distinguish the most probable violations. This field has been dependent upon progressing research in many areas of the planet. Machine-based wrongdoing examination frequently includes information assortment, grouping, design, distinguishing proof, expectation, and exhibit. Conventional information mining procedures-relationship examination, division and forecast, bunch investigation, and outer investigation-find designs in organized information, while new procedures distinguish patterns from both formal and casual information. The primary target of this work is to make a prescient model that can precisely foresee crooks.

It has been suggested in [7], that face reputation may be for a full or partial face, with the entire face taken into account for complete face detection and unique traits taken into account for partial face detection. In essence, this approach depends on an eyewitness's memory of the face and the sketch artist's precision in capturing those aspects. Therefore, even partial face recognition could benefit from a stronger algorithm.

The EvoFIT composite system was developed and tested as a standalone unit in [8]. Additionally, a tiny database of composites was created, which could be used to look for IDs that matched. It was discovered that feature shape details were significant EvoFIT, in the case of composites created with the recognition-based EvoFIT, while information on pixel intensity (texture) was for composites created by a typical feature-based approach. The outcomes are encouraging for the automatic development of facial composites and their recognition.

Developed a method for improving diverse face recognition scenarios, which allows for the automatic identification of forensic sketches and drawings when compared to a gallery of mug shots and a collection of mug photo images in [9]. Pre-processing and matching are the two stages of the suggested method. By aiming to enhance the forensic sketches that resulted prior submitted to their submission to the matching corresponding step, this work contributes to the pre-processing stage. The recommended computational method was based on applying geometric adjustments to the original forensic sketch's face areas to produce a population of sketches an assortment of sketches.

In [10], concentrated on facial recognition using composite sketches. First, it uses the AdaBoost algorithm to identify determine the facial mechanism and the face geometrical model to identify the face section. The Tchebichef moment invariant feature and Multi-scale Local Binary Patterns (MLBP) are used to extract features from each face feature. The ANN classifier is then trained to recognize the subject of the classification. The suggested approach makes use of ANN, which tends to overfit the training set. Overfitting is likely caused by several factors, including the fact that an ANN's size and structure are mostly decided by trial and error.

In [11], research proposes the system development for the recognition of forensic face sketches utilizing a computer vision technique, such as the Self-Organizing Map (SOM) Neural Network and the Two-Dimensional Discrete Cosine Transform (2D-DCT), both of which were simulated in MATLAB.

In feature-based matching, it is proposed to use a feature vector containing a feature image face (be it an image or a photograph) in terms of features from the grey level co-occurrence matrix (GLCM) and the Histogram of Oriented

Gradients (HoG) discussed in [12]. By computing the features in the first stage, the likelihood of precise matching is improved. To further reduce time and computational cost, an effective feature reduction approach is needed. Another choice is to concentrate on improving accuracy.

In [13], a stand-alone application that combines deep learning with cloud infrastructure is created to allow users to create composite face sketches of suspects without the use of forensic artists. Only a few situations—like matching face drawings to face pictures found in police records—are intended for it to be effective.

The [14] focus on using deep learning and other image processing methods, such as the Histogram of Oriented Gradients, to recognize real-life persons from hand-drawn sketches. Face sketch recognition has been built for a few instances with limited learning from a few photographs in this project. It's intended for use on a small scale, such as with a few photographs in a small database.

Using a deep graphical feature learning framework, the face sketch synthesis method developed by [15] combines generative exemplar-based techniques with discriminatively trained deep convolutional neural networks (dCNNs). In the future, optimum deep representations may be used to solve the identification issue.

The Authors [16] employ FaceNet, a pre-trained model (FN). The facial images are altered by FN into a compact Euclidean space where distances increase the face's nearness.

In [17], Proposed an approach that employs deep learning. The final phase entails training a classifier to be able to use a Python-based application to determine which individual is closest to a test image's measurements and output. To achieve the needed accuracy, the number of photos used during training must be increased. Unable to access by visually impaired people, hence text and audio features are required.

To solve the identification problem, [18] suggested a new face descriptor called Local Radon Binary Pattern to directly match faces in photographs and sketches of various modalities (LRBP). The face's form can be used to compute features that are resistant to variations in modalities between a face drawing and a photo. Face sketch recognition in situations where the eye-witness cannot accurately recall the facial due to severe face degradation. In actual circumstances, the most important requirement for the best outcomes is a facial sketch database produced from eyewitness memories.

A unique perception adaptive network (PANet) was proposed by [19]. It is made up of a face-adaptive fully convolutional encoder for hierarchical features, an extraction perception decoder for prospective facial area extraction, and a component-adaptive perception module for learning representations that are aware of facial components. The shapes of numerous synthesized. Under restricted conditions, sketches lack precision, and some edges are broken. It is therefore necessary to investigate contour-aware loss function optimization and contour-aware representation learning.

The modality gap was reduced during the feature extraction stage by [20] to build an intermodal face recognition algorithm. To record discriminative local face structures, a face description based on derived from linked information-theoretic encoding was used. In quantized feature spaces, the proposed linked information-theoretic projection tree enables coupled encoding and mutual information between sketches and photographs. Cross-modality issues are not taken into account. As a result, using the face descriptor to solve cross-modal variable problems puts efficiency at risk.

In [21], proposed a Face Sketch synthesis where a key branch of facial style conversion, produces face drawings of rendered images with the help of pairs of face-sketch images as a training database. Over the past two decades, various forms of drawing have been proposed. The model-based approach is an important component of existing integration methods. In this way, the training image and the sketch patches are integrated. Instead of directly using sketch patches, the filtered part of the high-pass training drawings is adopted to minimize the effect of the modality difference between the image and drawing. Then, a random offline sampling method to select a shared training image and patch drawings for a test image clip.

In [22], proposed current object recognition methods that use important machine learning methods. To improve its performance, larger data sets can be used, learning more powerful models, and applying best practices to prevent overcrowding. The following are some of this paper's contributions: The ILSVRC-2010 and ILSVRC-2012 competitions used ImageNet subsets for one of the biggest convolutional neural networks ever trained, yielding the best results ever recorded on these databases. Convolutional neural networks can be trained using a variety of functions, all of which are documented, including the excellent 2D convolution GPU.

In [23], the authors introduced a new algorithm for drawing a photo. The suggested approach diverges significantly from those that have been published because it uses a feature-based presentation to compare drawings and images. Previous methods have made complete comparisons only in drawings that have been transformed into images (or vice versa) using direct line conversion on a solid image or by producing a synthetic image. Because the proposed matching algorithm is similar to a local feature, it can be used in conjunction with the integrated algorithm to blend the mixture.

A face-to-face search approach based on drawings was proposed by [24]. Match-to-mugshot matching and personal photo search employing connected, tailored, and enhanced feedback make up the two-stage technique. Employing the linked answer in the second section, this study offers a personal face search algorithm using the ldquo human-in-the-loop rdquo notion. From the user, good and terrible samples were taken. The next step is to create and develop a response algorithm that uses discriminatory analysis of the line under the online learning space for comprehensive facial representation.

A new method of technique for recognizing photos and sketches has been presented in [25], based on the Local Feature-based Discriminant Analysis (LFDA). Three distinct datasets were used to evaluate and compare this unique approach to its predecessors, and an additional gallery of 10,000 photographs was added to widen the gallery. Results of tests performed on the CUFS and CUFSF datasets show that our technique outperforms the opposition. Our method, which employs forensic sketching, also yields successful results. A size restriction is the dataset's small size. Our testing has shown that improving the training dataset improves our method's precision.

The problem with all of the proposed algorithms was, comparing facial sketches to human faces, whereas human faces are frequently face-front and so easy mapping in both drawn sketches and as well as photographs of human faces. However, the algorithms had a lower likelihood of mapping and matching a front-looking face from the database with a picture or sketch that included faces pointing in a different direction. However, the majority of these systems make use of image-extracted facial characteristics, chosen by the operator based on, account witness and then combined to make a single human face. There are even methods being developed for the generation of composite faces. Because each facial characteristic was taken from a distinct face shot with varying dissimilarities, it is challenging for both humans and any machine to match the facial traits with a criminal face.

All previous techniques are either ineffective or cumbersome and time-consuming. In addition to addressing the drawbacks of the aforementioned proposed techniques, our application, as previously mentioned, would also close the gap between the conventional hand-drawn face sketch technique and the new modernized composite face sketch technique by enabling users to upload hand-drawn face sketches and facial features.

3. Design and Implementation

The login page has a two-way locking system, and only the authorized person can log in to the module. Once the login is successful, the user is provided with the upload or create sketch module. Either a composite sketch can be created or, if it is already present, it can be directly fed into the feature extractor. The creation of the composite sketch is facilitated by selecting appropriate facial features and rendering the same image, then proceeding with feature extraction and entering the face recognition module, which refers to the criminal database and produces the outcome.

When the rough sketch is not present, the system enters the Creation of the Composite sketch module. The module begins with the selection of head shape, followed by selecting multiple features as mentioned by the eye-witness in a loop and once the sketch is completed, the Module Face Recognition Module receives the finished sketch. Inside the Face Recognition Module, the sketch is compared with the database in the server. Similarity is displayed on the screen. If a matching face is detected, details about the suspect are displayed along with other metadata. Our application is made in a way in which the authoritative person can use the application without any necessary background in the Computer Science field. No text commands are extensively required to use the application. Our work mainly consists of two modules:

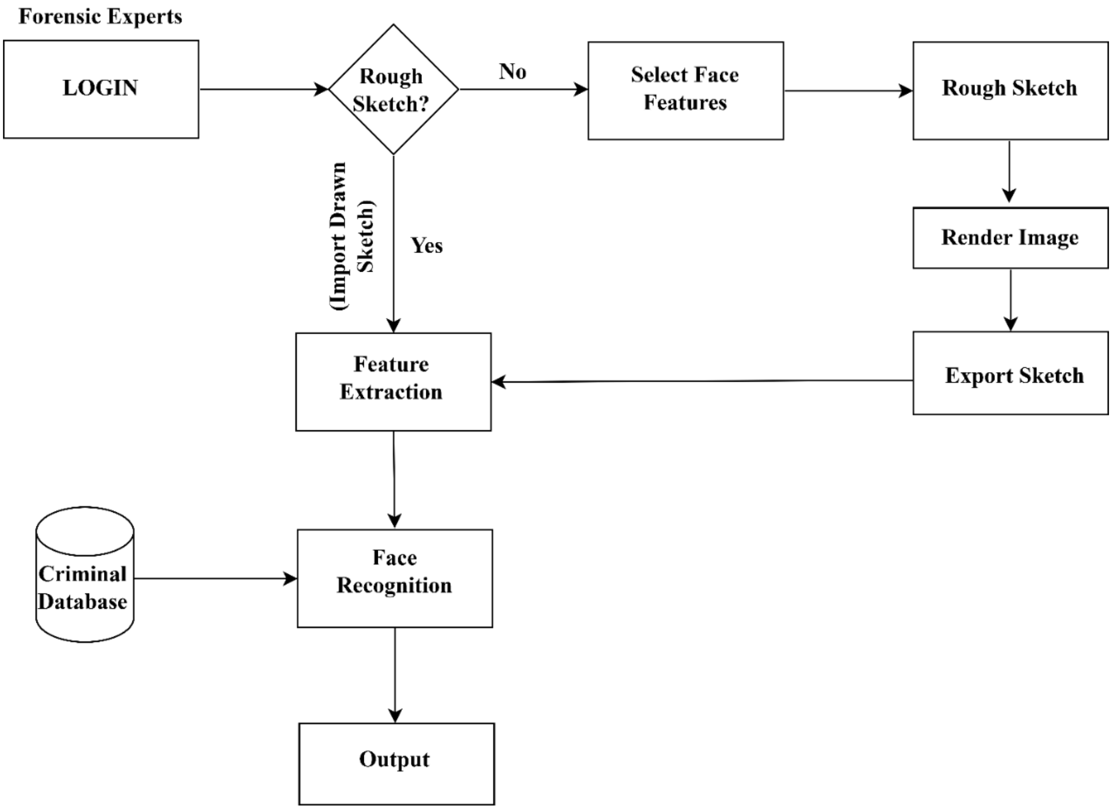


Fig 1. Proposed Model

1.1. Face sketch construction module:

The sole purpose of the dashboard is to promote the completion of no professional training before using this platform, and save your department time and resources. The flowchart above illustrates how the platform follows the user's instructions to produce a precise sketch of the face based on description. By maintaining it simple, it is made sure that the descriptions be able to be used by any member of the law enforcement branch given by the eyewitness without needing a skilled sketch artist from the forensic section. In rare circumstances, the eyewitness might even be competent enough to use the platform, although that is not advised or recommended as it can jeopardize security measures.

The dashboard is composed of five essential sections. The canvas, which is seen in the centre of the dashboard and contains parts used to build the facial sketches, is the first and most important module. If every face element were displayed at once and in any order, the user would be unable to develop a precise face sketch that would be opposed to the objectives of the suggested system. We aimed to group the facial components into the facial categories that they fall under, such as the head, nose, hair, eyes, etc. to address this issue. Users would be able to use the platform to interact and produce the facial sketch much more easily as a result. Users can access several different face structures by choosing the category of the face in the left-hand column of the canvas dashboard.

A new module that appears on the right side of the canvas will allow the user to select a facial element from a list of facial elements to sketch a face once the user has selected a specific facial category. You can judge based on eyewitness testimony.

On the canvas, the elements are positioned in a specific area and order, so that the eye elements would be regardless of the sequence in which they were chosen, the element was positioned over the head. Once selected, the elements are displayed on the canvas and can be repositioned in accordance with the description of an eyewitness to produce and a better and more exact sketch identical to every aspect of the face. The final element is the dashboard choices. For instance, if a user chooses an element they should not have, they can erase it by selecting the delete option that is accessible using the left panel's face category selection. The panel to the right of the dashboard contains the most important controls as well as a button that may be used to completely clear the canvas of the dashboard and make it empty. With the push of a button, you can save your finished face sketch as a PNG file for later access. Depending on the Law Enforcement Department, this may be located anywhere on the server or host computer.

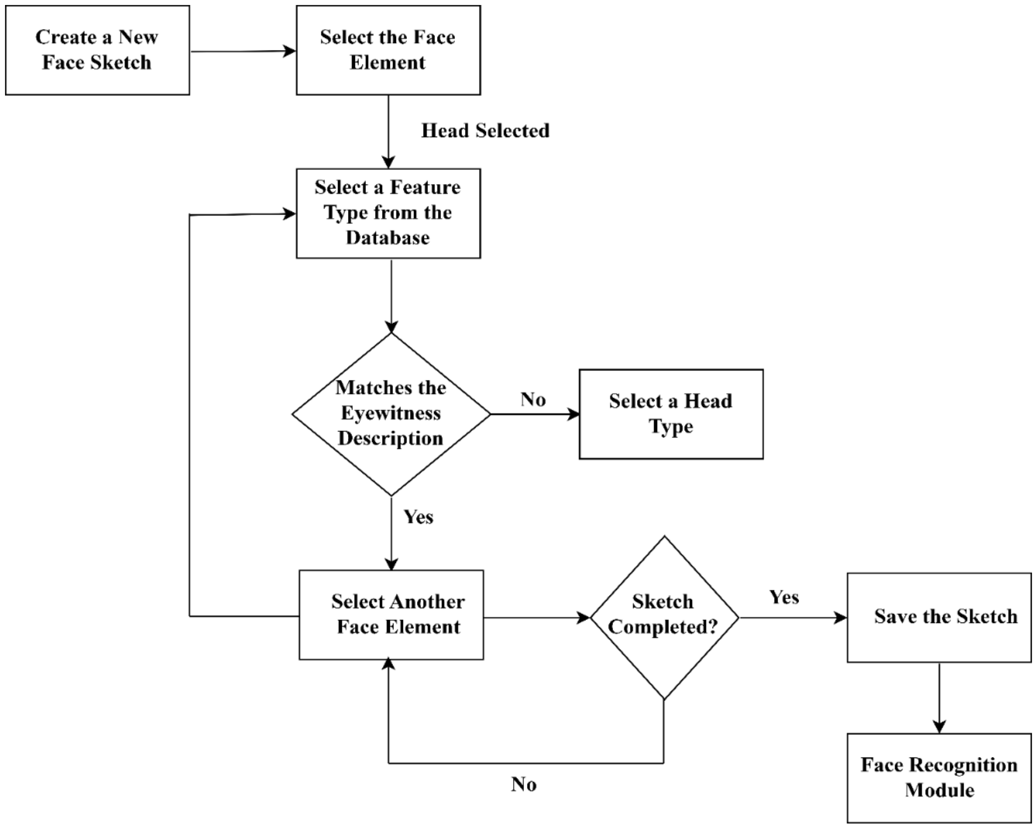


Fig 2. An application flowchart for making sketches

1.2. Face Sketch Recognition Module

Dashboard goal is to simply encourage users to use the platform without first completing any kind of professional training, saving the Department time and resources. The flowchart up above illustrates how the platform followed the user's instructions to produce an accurate facial image as per the description.

By keeping it simple, it assures that anyone in the law enforcement community may use the eyewitness information the need for a trained sketch artist from the forensic section. In rare circumstances, the eyewitness might even be able to manage the platform, albeit doing so is not recommended because it could jeopardize the security measures. The Figure 4 below illustrates the platform that displays everything and the matched person.

The Figure 3 demonstrates how the first step before using the platform to recognize faces is to prepare the already-existing records with the law enforcement department for it by teaching the platform's algorithm to recognize and assign IDs to the user's face photos in the already-existing records with the law enforcement department. The platform's algorithms link to the data, break down each face snapshot into a number of smaller features, and then assign unique IDs to each of these features in order to achieve this. The platform displays the matched face along with the similarity% and other data-derived attributes about the person after mapping the sketch, matching the face sketch with the records, and determining a match. The Figure 4 below illustrates the platform that displays everything and the matched person.

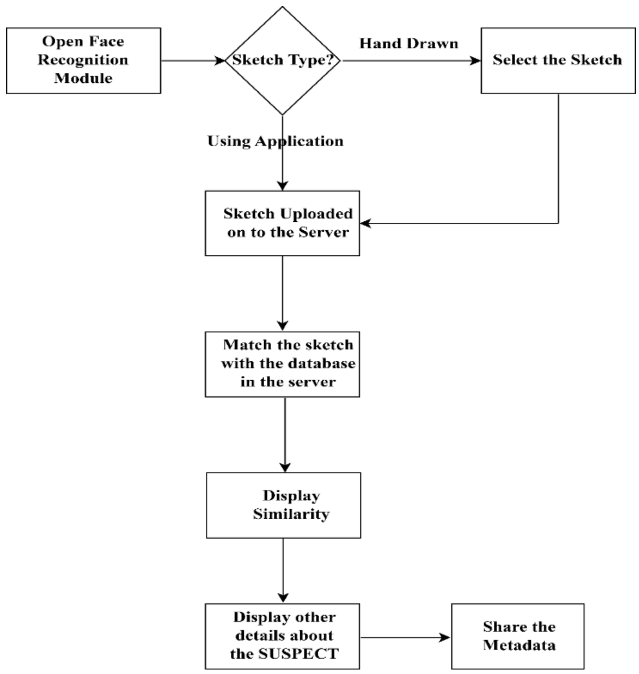


Fig 3. Flowchart for recognizing a sketch in the application

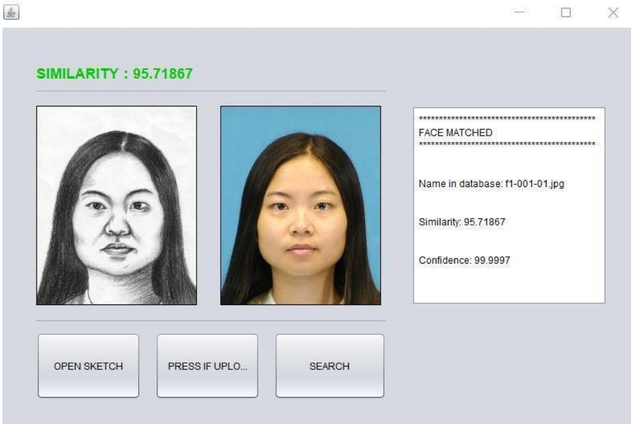


Fig 4. Face Sketch matched to Database Record

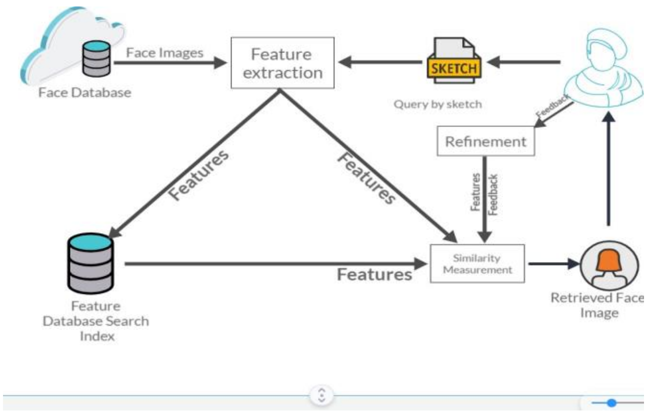


Fig 5. Implementation View

Each face image in the database is processed offline by FSR to extract visual elements like shape, texture, and spatial information. As a result, a feature database—a distinct data collection—stores and indexes a computational description known as an image signature. The investigator can use the internet technique to look for and find face photographs that resemble a query sketch. This interactive search technique can be accomplished in two steps: initially, query sketch's features can be extracted using the same method as above, and then the query sketch and its features can be compared using a specific similarity algorithm. The ranking of similarity or classification of the photos can then be done using the similarity algorithm's value. In order to extract pertinent aspects from a face and sketch, FSR uses descriptors. The study divided feature descriptors into visual and semantic categories. Visual features can, on the one hand, be universal or industry-specific. Global or local visual aspects are both possible. The investigator is then shown it. Explanation of the Algorithm and how it is being implemented in Fig. 6.

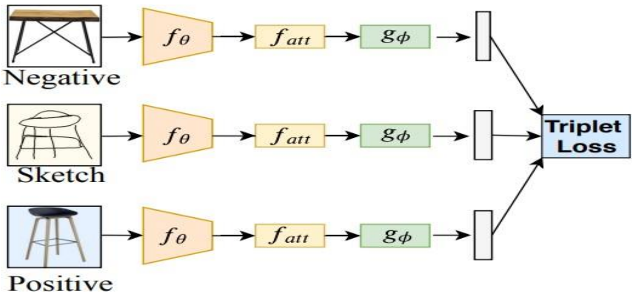


Fig 6. Flow of the Algorithm

A state-of-the-art Siamese network with three CNN [26-29] branches with common weights is used for pre-training (see Fig. 6). Each branch represents a query sketch, a positive photo, and a negative photo. Following modern sketch feature extraction methods, we use mild spatial attention to focus on key regions of the feature map. Our basic model consists of three different modules. fatt is modeled by a 1x1 convolution followed by a softmax operation, and g is a final fully connected layer with l2 regularization that produces an embedding of size D. f is initially set using InceptionV3 weights of pre-trained values. The attention module's output is computed by Batt = B + B fatt given the feature map B = f(I)(B).

The final feature representation required for distance calculation is then obtained by global average pooling using a vector representation that is again fed into g. We regarded f, fatt, and g as being enveloped in an all-encompassing embedding function F. The training data consists of three triplets, a, p, and n, each of which contains a sketch anchor and positive and negative pictures. The model is trained using triplet loss, which seeks to increase the distance between the sketch anchor and the negative photo and decrease the distance between the sketch anchor and the positive photo. The triplet loss can therefore be expressed as follows: max 0, + +, are the margin hyperparameter. Edge extraction is used in numerous ways by SBIR and the associated work of classifying sketched images to align the statistics of the sketch and photo distributions. Triplet loss CNNs have been identified as a suitable model for SBIR embedding in recent SBIR research.

1.3. We followed the following training stages

To create a unified 256 x 256 input data set, images of the photo are first downsized while maintaining the aspect ratio to have a maximum dimension of 256 pixels. The bounding box longest side for sketches in 256 x 256 canvas is fixed at 200 pixels. As the training process uses several drawing datasets with potentially different stroke thicknesses, all sketches are skeletonized using the morphological thinning method to have a 1-pixel stroke width.

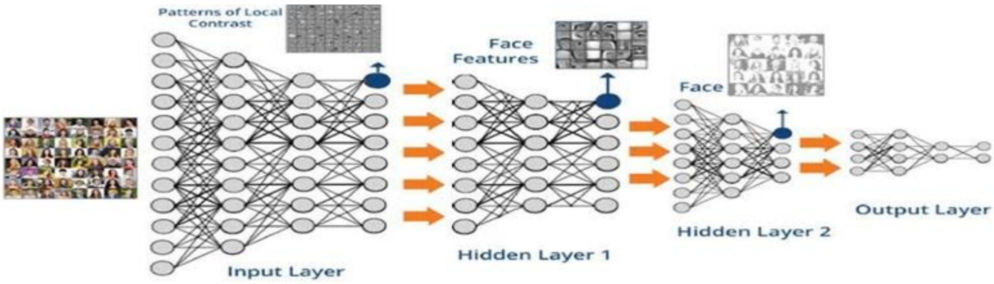


Fig 7. CNN Model for Sketch Based Image Retrieval

An exception is the application of random inversion in step 4 when the fine-grained Sketchy dataset is used. The random inversion is performed simultaneously with the positive anchor pair to obtain the fine-grained features. Since the scaling scale [0, 9, 1, 1] and rotation range [5, 5] are both quite small and can compensate for the inaccuracy of the alignment between the photos and their corresponding sketches, we do not perform the random rotation and scaling. Since the selection of instance-level triplets in Phase 4 is already difficult enough for the training to converge successfully, we did not apply hard negative mining.

1.4. Information about the implementation of Modules

When building our models, we used the OpenFace library. In contrastive and triplet networks, random pairs of anchor-positive and anchor-negative are chosen for training (stage 2 and beyond). Pairs or triplets may exist at the instance level (positive photos have the same category name as the anchor and negative images belong to a different category), depending on the data set, or at the category level (positive images have the same category label). Similar object and instance labels to the negative image, but distinct examples under the same category. We chose category-level pairs for level 2 and category-level triples for level 3 since the TU Berlin class dataset only enables category matching. For Stage 4 Sketchy dataset, we combined category and instance-level data in triplet construction. A given training sketch has a 20% chance of producing a category triplet and an 80% chance of producing an instance-level triplet. This aids in learning that are representative both within and across categories. While the principle behind our approach is similar to those of quadruplet networks, we implement it via data selection rather than by creating a new loss function and quadruplet input format.

4. Results and Inference

As one can see in figure 8 represents model accuracy vs epoch curve. As it is clearly visible through the graph, the model accuracy increases with an increase in the epoch.

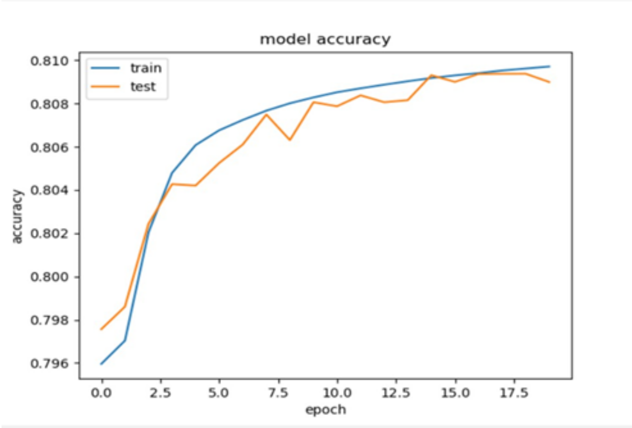
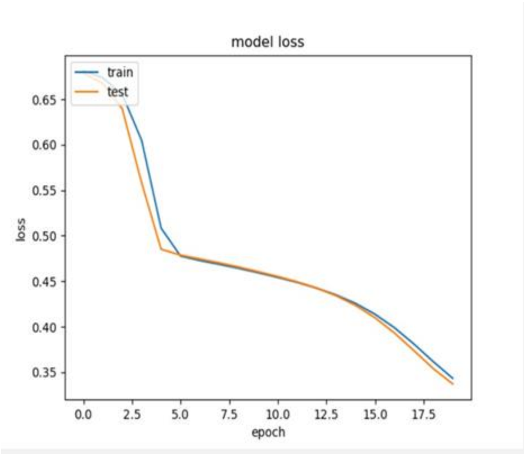
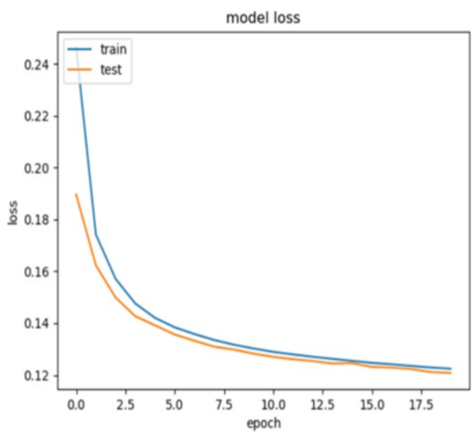


Fig 8. Model Accuracy



(a)



(b)

Fig 9. Comparison results for Model Loss

In figure 9, the left graph we obtained when we train and tested are model with fewer numbers of image sets, so it is having a high amount of model loss that's why showing less accuracy. After that we're training and tested using 10000 images of which around 1000 images came to be duplicated so discarded and rest we took 9000 images in the ratio of 7:3(6000-3000) ratio to train and test the model which resulted in 81% accuracy as shown in model accuracy versus epoch curve.

A dashboard with the eye element selected shows different eye shapes. The authenticated user can choose the required eyebrow shape as described by the eye-witness as shown in figure 10. The authenticated user can choose the required nose shape as described by the eyewitness. Dashboard with the Lip Element selected, illustrating the various lip shapes. The authenticated user can choose the required lip shape as described by the eyewitness.

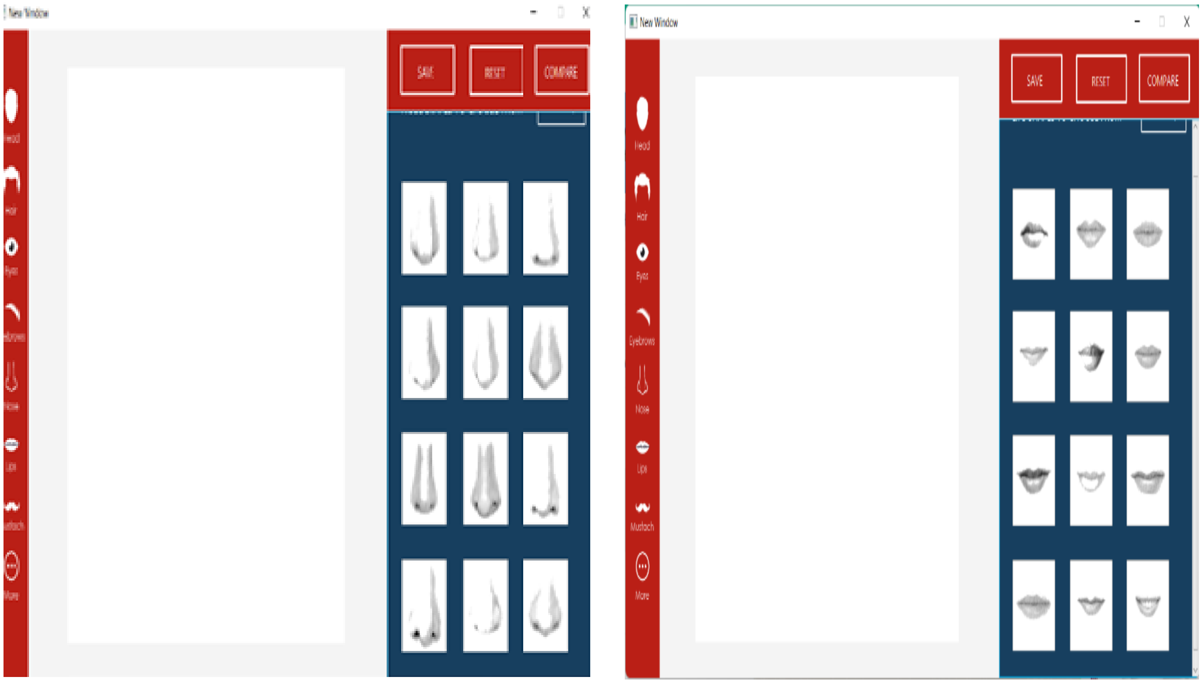


Fig 10. Dashboard to Create a Facial Sketch Dashboard with the Nose Element Selected showing the various nose shapes

Dashboard with the Facial Hair Element selected, displaying the various Stache and Beard shapes. The authenticated user can choose the required element as described by the eye-witness as shown in figure 11. Dashboard with the Ear and Neck Element Selected showing the various ear and neck shapes. The authenticated user can choose the required element as described by the eye-witness.

The Hairstyle as described by the eye-witness is selected and displayed on the dashboard canvas as shown in Figure 12. The head shape and eye shape as described by the eye witness is selected and displayed on the dashboard. The Nose and eyebrow shape as described by the eye-witness is selected and displayed on the dashboard canvas.

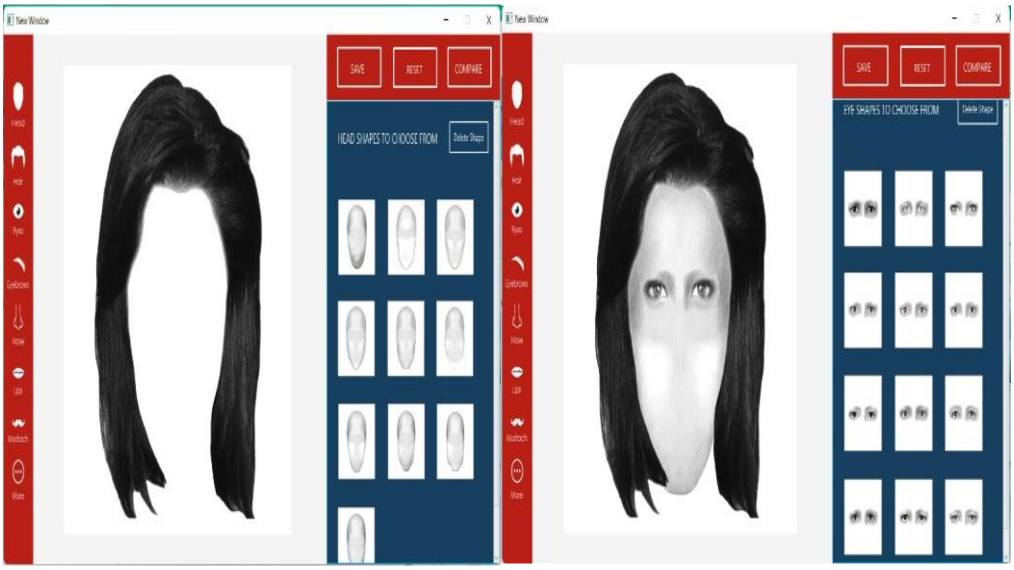


Fig 12. Head and eye shape selected in Dashboard

Fig 13. The created face-sketch is being saved in the computer

The face-sketch created with the description of the eye-witness is saved in the required format in the system of the authenticated user as shown in figure 13. Figure 14 shows the options page for Open sketch, upload sketch, and search buttons in the Upload sketch Module of the authenticated user's System. The below figure 15 shows that the image sketch has been successfully uploaded to the standalone application which is now ready to search for a matching face in the database.

Fig 14. Upload sketch splash screen

By taking a variety of images in consideration, ensuring whether the model can keep up with the variations or not. Images with Different Background in database: By feeding the database with images having slightly varying background in order to get accuracy. Checking the same image with drop down as well as handmade sketch: We have tried the model on both drop down and handmade sketch in order to check whether the model is coordinating well with the drop down feature. Face sketches when matched with police database records will show more detail with similar quotient as shown in figure 15.

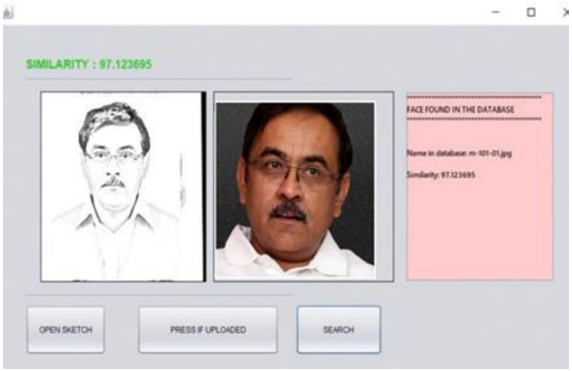


Fig 15. Face Sketch matched to the Database record

5. Conclusions

The work "A Deep Learning-Based Approach for Identification and Recognition of Criminals" is currently only intended to function in a select few scenarios, such as matching on-face sketching with facial photos in law enforcement databases. The platform will likely expand significantly in the future to accommodate different scenarios and technologies, enabling it to investigate a range of media and surveillance channels and obtain a far wider range of results, You can customize the platform to match your sketch to the human face in your video feed using 3D mapping and imaging technology. The same method can be applied to his CCTV surveillance to execute facial identification on live CCTV footage. The platform can work better with social media as it serves as a rich source of data in modern society. This method would enhance the capability of the platform to discover a match for increasing accuracy while accelerating the process. The platform might have features that make it stand out from all other relevant studies and suggested solutions in this field when compared to past studies on the issue. These features would increase the platform's overall security and accuracy.

Acknowledgment

Authors acknowledge the support from M.S. Ramaiah Institute of Technology and REVA University for the facilities provided to carry out the research.

Conflicts of interest

The authors declare no conflicts of interest.

Author contributions

Mohana Kumar S, Sowmya B J were identified Initial problem identification, algorithm write-up, analysis, drafting of the manuscript, and simulation. **Kavitha H, Dayananda P S** were responsible for the Literature survey and helped in the initial review process. , **Manjunath R** was responsible for the Complexity analysis of the research, and evaluation of the research work. **Supreeth S, Shruthi G** were responsible for the figures, final formatting, and applied for the journal. All authors worked together to implement, evaluation and approve the final version of the paper.

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