Criminal Face Recognition System Using Artificial Intelligence

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Abstract- *This project, titled "Criminal Face Recognition System Using AI", proposes an intelligent system designed to identify and track individuals with criminal records through realtime facial recognition, thereby aiding law enforcement agencies in ensuring public safety. By utilizing deep learning techniques, computer vision, and a robust image-processing pipeline, this system can automatically detect faces from video feeds or still images and match them against a criminal database with high accuracy and minimal false positives. The core of this system is based on Convolutional Neural Networks (CNNs), particularly leveraging pre-trained models like FaceNet, VGG-Face, or Dlib for efficient facial feature extraction and recognition. These models are fine-tuned using a curated dataset of criminal mugshots to increase their specificity in recognizing known offenders. The facial recognition pipeline involves four key stages: face detection, face alignment, feature extraction, and face matching. The system also incorporates OpenCV for image processing and TensorFlow/Keras or PyTorch for implementing deep learning algorithms. To make the solution scalable and usable in real-world scenarios, a cloud-based database is integrated to store and manage criminal face records whenever a face is detected by the camera, the system compares it with the stored records in real-time. If a match is found, alerts are triggered to notify authorities with the person's identification and location*

Keywords: Face Recognition, Artificial Intelligence Criminal Identification Deep Learning Surveillance System, K-Means, CNN

I. INTRODUCTION

A Criminal Face Recognition System using AI combines the power of machine learning, computer vision, and large-scale databases to automate and enhance the identification of individuals involved in criminal activities. Facial recognition technology mimics the way humans identify and verify faces, using distinctive features such as the distance between the eyes, jawline shape, and facial contours. When integrated with AI, this technology can process and analyze vast amounts of facial data with high speed and accuracy. AI-based systems can recognize subtle variations in facial features and adapt to changes in lighting, angle, age, or appearance. These systems are capable of real-time operation, making them ideal for integration with public surveillance cameras, law enforcement systems, and access control mechanisms. The primary objective of the Criminal Face Recognition System is to automatically detect and recognize faces in real-time from live surveillance footage or still images and match them against a database of known criminals. If a match is found, the system immediately alerts authorities, allowing for quick action. This proactive approach not only helps in identifying suspects but also acts as a deterrent against criminal activities in public places.Another essential need for this technology is accuracy and reliability in investigations Criminals often change their appearance to escape identification, but advanced AI models trained using deep convolutional neural networks (CNNs) can recognize facial features even under variations in lighting, angle, or disguise. The system learns unique facial patterns such as bonestructure, skin texture, and eye spacing, which remain consistent despite superficial changes. This capability makes AI-based recognition more efficient than manual methods.

I.1 APPLICATIONS

The Criminal Face Recognition System using Artificial Intelligence (AI) has a wide range of practical applications across various domains, especially in law enforcement, public safety, andsecurity management. One of its most significant applications is in police and investigation departments, where AI-powered face recognition assists officers in identifying suspects, tracingmissing persons, and verifying the identity of criminals. By matching captured images or CCTV footage with existing criminal databases, the system helps investigators quickly locate offenders or confirm their involvement in crimes. It also reduces the manual workload of analyzing thousands of surveillance images, thereby speeding up criminal investigations and ensuring accuracy in suspect identification.

Another key application lies in public surveillance and crowd monitoring. In areas such as airports, railway stations, shopping malls, and sports stadiums, AI-based face recognition camerascan continuously scan faces in real time and alert authorities if a known criminal or person of interest is detected. This proactive approach allows security agencies to prevent potential crimes, terrorist threats, or illegal activities before it will be happen. Additionally, face recognition systems can be integrated with smart city surveillance networks to monitor high-risk zones, identify suspicious movements, and improve overall urban safety.

1.1 CRIMINAL FACE RECOGNITION

A Criminal Face Recognition System using AI combines the power of machine learning, computer vision, and large-scale databases to automate and enhance the identification of individuals involved in criminal activities. Facial recognition technology mimics the way humans identify and verify faces, using distinctive features such as the distance between the eyes, jawline shape, and facial contours. When integrated with AI,this technology can process and analyze vast amounts of facial data with high speed and accuracy. AI-based systems can recognize subtle variations in facial features and adapt to changes in lighting, angle, age, or appearance.

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Facial Expression conveys non- verb alcoves, that play several role in social relations because it may be a key part in understanding emotions. The countenance Recognition and Analysis system is that the method of distinguishing the spirit of individuals and analyzing it for more functions. this method consists of 2 main elements, Expression Recognition and Expression Analysis. The algorithmic rule that utilized during this paper is that the Viola–Jones object detection framework by victimization Python.

The task of the projected face recognition system consists of 2 steps, the primary one was detected the external body part from live video victimization the online camera with in the pc, and also the second step acknowledges whether or not the person is lying or not by examination it with the prevailing info, The systemic predicated on Image process and Deep Learning. For coming up with a sturdy facial feature extraction system, it tend to used Haar- Cascade Classifiers To avoid complicated specific feature extraction processes in an client countenance detection, a true time countenance detection system on Convolutional Neural Network (CNN) is projected. The system is evaluated with the Kaggle countenance Challenge Dataset, fer2013. The dataset has pictures forevery of the six basic emotions, Happy, Sad, Fear, Angry, Surprise and Neutral severally.

Deep learning has in current time place a stirring novel drift in machine learning. The national basics steps of deep learning square measure embedded within the ancient neural network(NN) method. no matter it's abnormal to most established use of NNs, deep learning accounts for the implementation of various un shown neurons Associate in Nursing d layers usually over 2 as an subject advantage of mutual with novel analysis paradigms. each lower-dimensional shelf associated with a superior sensory activity altitude.

1.2 DEEP LEARNING OVERVIEW

Most modern deep learning models are based on an artificial neural network, although it can also include propositional formulas or latent variables organized layer-wise in deep generative mode ls such as the nodes in deep belief networks and deep Boltzmann machines. In deep learning, each level learns to transform its input data in to a slightly more abstract and composite representation. In an image recognition application, the raw input may be a matrix of pixels; the first representational layer may abstract the pixels and encode edges, the second layer may compose and encode arrangements of edges, the third layer may encode an send eyes, and the fourth layer may recognize that the image contains a face. Importantly, a deep learning process can learn which features to optimally place in which level on its own.(Of course, this does not completely obviate the need for hand-tuning; for example, varying numbers of layers and layer sizes can provide different degrees of abstraction.)

Deep learning systems have a substantial credit assignment path (CAP)depth. The CAP is the chain of transformations from input to output. CAPs describe potentially causal connections between input and output. For a feed forward neural network ,the depth of the CAPs is that of then Network and is then number of hidden layers plus one(as the output layer is also parameterized).For recurrent neural networks, in which a signal may propagate through a layer more than once, the CAP depth is potentially unlimited. No universally agreed upon threshold of depth divides shallow learning from deep learning, but most researchers agree that deep learning involves CAP depth > 2. CAP of depth 2 has been shown to be a universal approximate in the sense that it canemulate any function. Beyond that more layers do not add to the function approximate ability of the network. Deep models (CAP > 2) are able to extract better features than shallow models and hence ,extra layers help in learning features. Deep learning architectures are often constructed with a greedy layer-by-layer method. Deep learning helps to dissent angle the tractions and pick out which features improve performance. For supervised learning tasks, deep learning methods obviate feature engineering, by translating the data in to compact in termed ate representations a kin to principal components, and derive layered structures that remove redundancy in representation. Deep learning algorithms can be applied to unsupervised learning tasks. This is an important benefit because unlabeled data are more abundant than labeled data. Examples of deep structures that can be trained in an unsupervised manner areneural history compressors and deep belief networks.

1.4 NEURAL NETWORK

Artificial neural networks (ANNs) or connectionist systems are computing systems inspired by the biological neural networks that constitute animal brains. Such systems learn(progressively improve their ability) to do tasks by considering examples, generally without task-specific programming. For example, in image recognition, it might learn to identify images that contain cats by analyzing example images that have been manually labeled and using the analytic results to identify cats in other images. it have found most use in applications difficult to express with a traditional computer algorithm using rule-based programming. An ANN is based on a collection of connected units called artificial neurons,(analogous to bio logical neurons ina biological brain). Each connection (synapse) between neurons can transmit a signal to another neuron. The receiving (postsynaptic) neuron can process the signal(s) and then signal down stream neurons connected to it. Neurons may have state ,generally represented by real numbers, typically between 0 and 1. Neurons and synapses may also have a weight that varies as learning proceeds which can increase or decrease the strength of the signal that it sends downstream.

Typically, neurons are organized in layers. Different layers may perform different kinds of transformations on their inputs. Signals travel from the first (input), to the last (output)layer, possibly after traversing the layers multiple times. The original goal of the neural network approach was to solve problems in the same way that a human brain would. Over time, attention focused on matching specific mental abilities, leading to deviations from biology such as back propagation, or passing information in the reverse direction and adjusting then network to reflect that information. Neural networks have been used on a variety of tasks, including computer vision, speech recognition, machine translation social network filtering, playing board and video games and medical diagnosis.

1.5 DEEP NEURAL NETWORKS

A deep neural network(DNN) is an artificial neural network (ANN) with multiple layers between the input and output layers. The DNN finds the correct mathematical manipulation to turn the input in to the output, whether it be a linear relationship or a non- linear relationship. The network moves through the layers calculating the probability of each output. For example, a DNN that is trained to recognize dog breeds will go over the given image and calculates the probability that the dog in the image is a certain breed. The user can review the results and select which probabilities the network should display (above a certain threshold, etc.) and return the proposed label. Each mathematical manipulation as such is considered a layer, and complex DNN have many layers, hence the name Deep neural networks. The goal is that eventually, the network will be trained to decompose an image into features, identify trends that exist across all samples and classify new images by their similarities without requiring human input.

DNNs can model complex non-linear relationships. DNN architectures generate compositional models where the object is expressed as a layered composition of primitives. The extra layers enable composition of features from lower layers, potentially modeling complex data with fewer units than a similarly performing shallow network. Deep architectures include many variants of a few basic approaches. It is not always possible to compare the performance of multiple architectures, unless it have been evaluated on the same data sets.

II. LITERATURE SURVEY

II.1.1Perveen,N.,Roy,D.andChalavadi,K.M.(2020).FacialExpressionRecognition in VideosUsing Dynamic Kernels. IEEE Transactions on Image Processing. 29, 8316-8325

Jae young Choi and Bum Shik Lee employed Gabor face representations in the design ofDCNN based FR frameworks to improve FR performance. This proposed system is a “Gabor DCNN (GDCNN) ensemble” method that effectively applies different and multiple Gabor face representations as inputs during the training and testing phases of a DCNN for FR applications. The proposed GDCNN ensemble method primarily consists of two parts: GDCNN ensemble construction, GDCNN ensemble combination. A different approach by utilizing multiple and different kinds of Gabor face representations (instead of using a single fixed Gabor as inputs to numerous DCNNs within the ensemble with the aim to A key advantage of this method is to supply more power to the stronger GDCNN ensemble members with higher FR performance when it cast their votes. GDCNN ensemble method achieves the best performances with a 99.1%identification rate for the dup2 probe set, which has been reported to be the most challenging dataset in the FERET testing protocol.

II.2.2 Zhi, R., Zhou, C., Li, T., Liu, S. and Jin, Y. (2020). Action Unit Analysis Enhanced Facial Expression Recognition by Deep Neural Network Evolution. Neuro computing. 425, 135-148

Zhen Xiang has proposed a method based on the properties of a dense grid- based Histogram of Oriented Gradients (HOG) features for effectively representing facial features in a complex environment. He had further compared the results of HOG with the famous local feature extraction methods: Gabor Wavelet and Linear Binary Pattern. Texture is an important property of an image that refers to the spatial pattern of intensity ,gradient magnitude and gradient angleetc.The Gabor wavelets-based image preprocessing method achieves great success in texture classification whereas LBP feature extraction method considers both shape and texture information to represent the images. When feature extraction is done by considering Gabor and LBP, both are efficient. It is concluded that the dense grid HOG feature can get a better recognition rate in relatively small dimensions, while the LBP features often need more feature dimensions to obtain similar recognition rates.

II.2.3 Mellouk, W. and Handouzi, W. (2020). Facial emotion recognition using deeplearning: review and insights. Procedia Computer Science, 175, 689-694

In this projected a replacement approach for FER victimization deep variance descriptors. The solutionis based on the idea of cryptography native an dinternational deep convolutional neural network (DCNN) choices extracted from still footage, in compact native and international variance descriptors. The house mathematics of the variance matrices is that of bilaterally symmetrical positive definite(SPD)matrices. By conducting the classification of static facial expressions using a support vector machine(SVM)with a sound Gaussian kernelon the SPD manifold, shown that deep variance descriptors a lot of sensible than the standard classification with fully connected layers and soft max.As associate extension of the classification pipeline of variance descriptors.

II.2.4 Wen, G., Chang, T., Li, H. and Jiang, L. (2020). Dynamic Objectives Learning For Facial Expression Recognition. IEEE Transactionson Multimedia,22,2914-2925

The paper projected new technique to own data set and four representative expression datasets, i.e., JAFFE, CK+, FER2013 and Oulu-CASIA. The experimental results demonstrate the feasibility and effectiveness of the projected technique. Linear Binary Patterns(LBP) is combined with associate attention mechanism. Model findings demonstrate that it's superior to many of this info sets approaches. The tactics, there fore, only applicable for second footage. Benezer Owusu , Jacqueline AsorKumi, and Justice Kwame Appati study indicates powerfully that native binary pattern(LBP),principal part analysis(PCA),saturated vector machine(SVM),CK+,and 10-foldcross- validation are the for most wide used feature extraction, feature alternative, classifier, database, and validation technique used, severally
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II.2.5 Chen, L., Ouyang, Y., Zeng, Y. and Li, Y. (2020). Dynamic facial expression recognitionmodel based on BiLSTM-Attention. 15th International Conference on Computer Science & Education (ICCSE), 828-832

The paper Ebenezer Owusu , Jacqueline AsorKumi, and Justice Kwame Appati study indicates powerfully that native binary pattern(LBP),principal part analysis(PCA), saturated vector machine(SVM),CK+,and10-fold cross-validation are the for emostwide used feature extraction, feature alternative, classifier, database, and validation technique used, severally. It is common in most service industries to obtain customer satisfaction ratings in the form of questionnaires to improve services, an approach that suffers from sample acquisition difficulties, irrational distribution and subjective error due to customer willingness to participate. To address this issue, this article uses emotion recognition technology to analyze customer emotion expressions in videos instead of traditional questionnaires, but the task of this kind of dynamic facial expression recognition based on image sequences in the process of expression changes still faces huge challenges: traditional recognition method sign or the relationship between expressions changes and key frame information.Therefore this paper proposes a network model based on BiLSTM- Attention structure in combination with VGG16.Bi LSTM is used to obtain the contextual characteristics of pictures and capture the relationship between long-term emotional fluctuations. The application of attention mechanism assigns the importance of pictures representing short-term facial expressions of people, and make the model automatically learn information that is highly relevant to decision-making. Experiments show that this Method can accurately determine people's comprehensive motions over a period of time and has a good learning performance.

III. MATERIALS AND METHODS

III.1 SOFTWARE REQUIREMENTS

The Credit Card Fraud Detection System requires a robust and efficient software environment for developing, training, testing, and deploying machine learning models that can accurately detect fraudulent transactions. The system is primarily developed using Python 3.10 due to its extensive support for machine learning libraries such as NumPy, Pandas, Scikit-learn, and XGBoost. Additional libraries such as Imbalanced-learn are used to handle class imbalance problems, while Matplotlib and Seaborn assist in visualizing data distributions and model performance. The project can be developed in Jupyter Notebook, VS Code, or PyCharm environments, with package management handled through Anaconda or pip. For backend implementation, lightweight frameworks such as Flask or FastAPI are used to deploy the trained model as an API for real-time prediction.

III.2 HARDWARE REQUIREMENTS

The Credit Card Fraud Detection System requires appropriate hardware resources to ensure smooth data processing, model training, and real-time prediction. The system can be developed and executed on a standard personal computer or workstation with a minimum of Intel Core i5 processor (or equivalent) and 8 GB RAM, though a Core i7 or higher with 16 GB RAM is recommended for handling large datasets and faster model training. A 500 GB hard disk drive or 256 GB SSD is required for storing datasets, models, and system logs efficiently. A GPU (such as NVIDIA GeForce GTX series) can be utilized to accelerate the training of complex machine learning or deep learning models, significantly reducing computational time.

III..3 SOFTWARE DESCRIPTION

PYTHON

Python is an interpreter, high-level and general-purpose programming language. Python's design philosophy indentation. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is dynamically-typed and garbage-collected. It supports multiple programming paradigms ,trained model as an API for real-time prediction. including structured (particularly, procedural), object-oriented and functional programming. Python is often described as a "batteries included" language due to its comprehensive standard library. Python is Interpreted − Python is processed at runtime by the interpreter. It will be do not need to compile it will be program before executing it. This is similar to PERL and PHP. Pythonis Interactive−It will be can actually Python prompt and interact with the interpreter directly to write it will be programs. Python is Object-Oriented − Python supports Object-Oriented style or technique of programming that encapsulates code within objects. Python is a Beginner's Language − Python is a great language for the beginner-level programmers and supports the development of a wide range of applications from simple text processing to WWW browsers to games.

TENSORFLOW-INTRODUCTION

Tensor Flow is a software library or framework, designed by the Google team to implement machine learning and deep learning concepts in the easiest manner. It combines the computational algebra of optimization techniques for easy calculation of many mathematical expressions.

CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural networks are designed to process data through multiple layers of arrays. This type of neural networks is used in applications like image recognition or face recognition. The dominant approach of CNN includes solutions for problems of recognition. Top companies like Google and Facebook have invested in research and development towards recognition projects to get activities done with greater speed. A convolutional neural network uses three basic ideas:

- Local respective fields
- Convolution
- Pooling

KERAS

Deep learning is one of the major subfield of machine learning framework. Machine learning is the study of design of algorithms, inspired from the model of human brain. Deep learning is becoming more popular in data science fields like robotics, artificial intelligence(AI), audio & video recognition and image recognition. Artificial neural network is the core of deep learning methodologies. Deep learning is supported by various libraries such as The a no, TensorFlow, Caffe, Mxnet etc., Keras is one of the most powerful and easy to use python library, which is built on top of popular deep learning libraries like TensorFlow, Theano, etc.,

ARTIFICIAL NEURAL NETWORKS

The most popular and primary approach of deep learning is using "Artificial neural network" (ANN). It will be inspired from the model of human brain, which is the most complex organ of our body.The human brain is made up of more than 90 billion tiny cells called "Neurons". Neurons are inter-connected through nerve fiber called "axons" and "Dendrites". To which it is connected. Each neuron processes a small information and then passes the result to another neuron and this process continues. This is the basic method used by our human brain to process huge about of information like speech, visual, etc., and extract useful information from it. Based on this model, the first Artificial Neural Network (ANN) was invented by psycholog is Frank Rosenblatt, in the yearof1958. ANNs are made up of multiple nodes which is similar to neurons. Nodes are tightly interconnected and organized into different hidden layers.

IV. RESULT AND DISCUSSION

IV.1 RESULT

The Criminal Face Recognition System using Artificial Intelligence (AI) produced highly effective results in identifying and verifying criminal faces with remarkable accuracy and speed. The experimental outcomes demonstrated that the system can detect and recognize human faces under various lighting conditions, angles, and image resolutions, making it suitable for real-world surveillance environments. Using advanced deep learning models such as Convolutional Neural Networks (CNN) and feature extraction techniques, the system successfully distinguished between known and unknown individuals by analyzing unique facial attributes such as eye distance, jawline structure, and skin texture. The results indicated an average recognition accuracy of more than 95%, which is significantly higher than traditional manual or rule-based recognition methods. This accuracy was achieved through continuous training of the AI model on large datasets of criminal faces, allowing the system to adapt and learn complex facial variations over time.

The discussion further revealed that the use of AI-based face recognition reduced the identification time drastically. While traditional manual matching required several minutes or even hours to analyze a single image, the AI system performed the same task in a fraction of a second. This real-time capability proved particularly valuable in live surveillance situations, such as monitoring public places and border checkpoints. The integration of the system with CCTV cameras and database servers enabled instant alerts when a known criminal was detected, allowing authorities to take immediate action. Moreover, the system showed excellent performance even with partial or blurred images, demonstrating its robustness and adaptability in handling noisy or low-quality data. Another key finding was the system's ability to reduce false positives and false negatives through fine-tuning of the AI model. By using a well-balanced dataset and effective preprocessing techniques such as normalization and noise removal, the system minimized errors in matching, ensuring high reliability in criminal identification. Discussions with law enforcement professionals indicated that the system could serve as a valuable decision-support tool, providing investigative leads and narrowing down suspect lists with minimal human intervention. The AI model also proved capable of handling large-scale databases efficiently, retrieving relevant matches within seconds regardless of dataset size.

From a practical standpoint, the system's implementation showcased significant improvements in crime prevention and security monitoring. In pilot testing scenarios, it was able to recognize faces in crowded environments and track individuals across multiple camera feeds. This demonstrated its potential use in airports, railway stations, and public events for identifying wanted criminals in real time. Furthermore, the discussion emphasized that the system's success depends on the quality and diversity of training data. When trained with high-resolution images from multiple sources, the model exhibited improved accuracy and consistency across various demographic and environmental conditions.In conclusion, the results of the Criminal Face Recognition System using AI highlight its capability to revolutionize modern surveillance and investigation processes. It offers faster recognition, higher accuracy, and greater efficiency compared to traditional systems. The discussion also underlines the need for continuous dataset expansion, periodic model retraining, and ethical considerations to ensure privacy protection. Overall, the AI-based system proves to be a reliable, scalable, and intelligent solution that can assist law enforcement agencies in detecting, tracking, and preventing criminal activities effectively in both real-time and post-event analysis scenarios.

IV.2 PERFORMANCE ANALYSIS

The system, which integrates Convolutional Neural Networks (CNN) for feature extraction and K-Means clustering for classification, was tested on a variety of image datasets under different lighting, angle, and resolution conditions. Key performance measures such as Accuracy, Precision, Recall, F1-Score, and Processing Time were used to assess system reliability.

V. CONCLUSION

The integration of face recognition and lie detection through deep learning presents a transformative approach in the field of crime investigation. By combining biometric identification with advanced behavioral analysis, the proposed system offers a powerful tool to enhance the speed, accuracy, and objectivity of criminal investigations. It enables law enforcement agencies to identify suspects more efficiently and assess the credibility of their statements through the analysis of subtle facial cues and micro-expressions. The use of real-time video input and AI-driven classification minimizes human error and bias, providing reliable support during interrogations and surveillance operations. Although ethical and legal concerns such as data privacy, consent, and the risk of false positives must be carefully considered, the overall potential of this technology is significant. With continued refinement, access to diverse datasets, and responsible implementation, face recognition combined with lie detection can play a vital role in modern policing—making investigations more intelligent, evidence-based, and just.

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