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Enhancing Culprit Identification in Real-Time Video Surveillance using Deep Fine-Tuned Optimized Transfer Learning and Attention Mechanism

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Abstract : Facial acknowledgment has gotten to be a basic innovation with differing applications, extending from security and reconnaissance to client verification and personalization. Over a long time, profound learning, especially Convolutional Neural Networks (CNNs), has revolutionized computer vision, empowering exceptional headways in facial acknowledgment assignments. This ponder dives into the synergies of consideration instruments and exchange learning inside the setting of CNNs, particularly utilizing VGGFace—a broadly recognized CNN engineering pre-trained on a broad dataset of facial pictures. This pre-training prepares Visual Geometry Group (VGG) Face with the capacity to capture complicated facial highlights and designs successfully. The integration of consideration components improves the model's center on vital facial locales, moving forward acknowledgment accuracy. Leveraging exchange learning, the pre-trained VGGFace demonstration is fine-tuned on a particular facial acknowledgment dataset, capitalizing on the information and representations procured from the broader facial dataset. This amalgamation optimizes the precision and effectiveness of the facial acknowledgment framework, displaying the potential to assist headways in this basic innovation.

IndexTerms - Attention Mechanism, CNN, Transfer Learning, VGGFace.

I. Introduction

VGGFace transfer learning offers a powerful and efficient solution for face recognition, demonstrating the potential to achieve state-of-the-art results while minimizing the computational burden and data requirements. This research serves as a starting point for researchers and practitioners in the field of computer vision to explore and implement VGGFace transfer learning in their own face recognition applications. The key advantage of using VGGFace transfer learning for face recognition is its ability to handle variations in pose, lighting, and facial expressions while still producing reliable results. Additionally, this approach reduces the need for extensive data collection and the computational resources required to train a deep network from scratch.

In this research, we discuss the theoretical foundations of VGGFace transfer learning for face recognition and its practical implementation, including the fine-tuning process and model evaluation. Research highlights the advantages, limitations, and potential challenges associated with this approach and provides insights into strategies for overcoming these challenges. The presented results demonstrate the superior performance of VGGFace transfer learning in comparison to traditional face recognition methods, emphasizing the significance of leveraging pre-trained deep learning models for face recognition tasks.

A. Open Source Computer Vision (OpenCV):

OpenCV (Open-Source Computer Vision) stands as a powerful and versatile open-source library that has become a cornerstone in the field of computer vision. Initially developed by Intel, OpenCV has evolved into a community driven project, providing a comprehensive set of tools and algorithms for various computer vision tasks. Offering support for multiple programming languages, including C++, Python, and Java, OpenCV enables developers and researchers to efficiently implement a wide range of image and video processing applications. The library encompasses functionalities such as image manipulation, feature detection, object tracking, machine learning integration, and more. Its cross-platform compatibility, robust documentation, and continuous updates make OpenCV a go-to solution for professionals and enthusiasts alike in domains spanning robotics, artificial intelligence, and beyond. As an open-source initiative, OpenCV fosters collaboration and innovation, playing a pivotal role in advancing the capabilities and accessibility of computer vision technologies.

B. Convolutional Neural Networks (CNNs)

They have a place in a category of profound neural systems particularly made for errands including the investigation of pictures and computer vision. Here are several critical things to get a handle on approximately CNNs. CNNs are based on the human visual framework for their motivation and neural arrangement to recognize designs and shapes. This permits them to get it and decipher visual information in a comparative way to how people do it. Interconnected neurons can recognize and secure various leveled highlights from natural pixel information through learning. Convolutional layers are the establishment of CNNs, utilizing channels or parts to extricate highlights from input pictures. These channels are outlined to distinguish designs such as edges, surfaces, and shapes. As the organization advances, it gets to be able to learn progressively complicated and theoretical highlights. Pooling layers are habitually utilized after convolutional layers to diminish the estimate of included maps through down sampling and decreasing spatial measurements. This contributes to minimizing computation and increasing the network's flexibility to input varieties. The ultimate expectations are made by one or more completely associated layers after the arrangement. The high-level highlights extricated by past layers are utilized by these layers to produce yield, such as course probabilities in picture classification. CNNs (Convolutional Neural Networks) By sharing parameters (parts) over different areas of the input picture, it upgrades computational effectiveness. By sharing data, CNNs can learn highlights that are invariant to interpretation, a critical calculation in recognizing designs over distinctive zones of a picture. Huge datasets are utilized to prepare CNNs for errands such as picture classification, and they can be balanced for other errands with smaller datasets. The utilization of exchange learning has gotten to be broad and has come about in major progressions in an assortment of applications. CNNs are being utilized in an assortment of applications, such as picture classification, protest discovery, facial acknowledgment, restorative picture examination, and independent vehicles. They are too commonly connected in video investigation. They have been utilized in commonsense applications inside the normal environment. The ponder of dialect preparation and discourse acknowledgment. In arrange to prepare profound CNNs successfully, a noteworthy sum of information and computational assets are vital. Overfitting, which happens when the show learns unimportant points of interest in the data, could be a potential concern. Be that as it may, strategies such as dropout and regularization can help in tending to this issue. Over time, CNNs have been created and developed, with diverse plans such as LeNet, AlexNet, VGG, GoogLeNet, and ResNet all playing a part in improving execution and viability in their possess one of a kind ways.

C. Attention Mechanism

The Attention Mechanism has emerged as a pivotal innovation in deep learning, particularly renowned for its effectiveness in tasks involving extensive data sequences, such as natural language processing and computer vision. This technique facilitates targeted focus on specific elements within input data during model predictions, significantly enhancing overall performance and computational efficiency. Originally introduced in the context of neural machine translation, attention has witnessed widespread adoption in diverse domains of deep learning, including language modeling, question answering, and text classification. Its fundamental principle involves computing weighted sums of input data, with these weights dynamically learned during the training process. This enables the model to selectively prioritize crucial elements, allowing for a more nuanced and effective understanding of complex data. While attention mechanisms offer notable advantages, including performance improvement, reduced computational complexity, and simplified interpretability, they also present challenges. These challenges encompass potential computational costs, optimization complexities, and the risk of overfitting. As a powerful tool in the deep learning landscape, the Attention Mechanism demands careful consideration and strategic implementation for optimal results in various research and application contexts.

D. Transfer Learning

Exchange learning may be a machine learning procedure that has picked up monstrous notoriety and demonstrated to be profoundly successful in different spaces, counting computer vision, common dialect handling, and numerous others. This approach includes the exchange of information learned from one assignment or space to another, permitting models to use pre-trained data and adjust it to unused, related errands. It involves Knowledge Exchange: Exchange learning is established on the thought that information procured amid the preparation of one machine learning demonstration can be connected to a diverse, but related, issue. It permits the reuse of important bits of knowledge, highlights, and parameters from a source assignment to upgrade the execution of a target task. Source and Target Spaces: In exchange learning, there are regularly two spaces: the source space, from which information is exchanged, and the target space, which is the modern issue or errand you need to unravel. The source and target spaces ought to share a few fundamental structures or designs for exchange learning to be compelling. Inductive Exchange Learning: In this situation, a show prepared on the source space is adjusted (fine-tuned) to perform a related target errand. This frequently includes upgrading a few of the model's parameters while keeping others settled.

Transductive Exchange Learning: Here, information is transferred to particular occurrences within the target space, instead of to the demonstration. This could be seen in strategies like instance-based learning or one-shot learning. Exchange learning includes a wide extend of applications. In computer vision, pre-trained Convolutional Neural Networks (CNNs) are frequently utilized as highlight extractors for different image related errands. In normal dialect preparation, pre-trained dialect models (e.g., BERT, GPT) have illustrated the capacity to boost the execution of content classification, assumption examination, and language era errands. Exchange learning can altogether decrease the sum of labeled information and computational assets required to prepare a demonstration from scratch. It quickens the improvement of machine learning arrangements and regularly leads to way better results, particularly when information is restricted for the target errand. Whereas exchange learning can be an effective instrument, selecting a fitting source demonstrates and fine-tuning methodology can be challenging. Guaranteeing that the source and target spaces are adequately related is vital for effective information exchange. Now and then, the source and target spaces may not be the same. Space adjustment procedures point to bridging the crevice between these spaces by adjusting their dispersions to make strides in exchange learning. Exchange learning can also be seen as a portion of the broader concept of ceaseless learning, where models learn from a sequence of assignments and continue to adjust and improve over time. Exchange learning may be a valuable method in machine learning and counterfeit insights that permits models to construct upon the information procured from one setting and apply it to modern, related challenges. It has the potential to spare time and assets while upgrading the execution of models in a wide run of viable applications.

E. Transfer Learning with CNNs

Convolutional Neural Frameworks (CNNs) and trade learning are two closely related concepts in the field of profound learning, particularly inside the space of computer vision. Inside the setting of trade learning, CNNs can be utilized as extractors. The convolutional layers of a pre-trained CNN illustrate have learned to distinguish diverse low-level and high-level highlights in pictures. These highlights can be imperative for a wide run of computer vision errands, from address disclosure to picture classification. Trade learning incorporates taking a pre-trained exhibit, such as a CNN arranged on a colossal dataset (e.g., ImageNet), and altering it to an unmistakable but related errand. This could be especially important once you've got a limited entirety of data for the target task. To perform trade learning with a CNN, empty the related layers after the organization (which are task-specific) and supplant them with cutting-edge layers suited for your target errand. The pre-trained convolutional layers are held and serve as highlight extractors. These layers capture common picture highlights that can be vital over different errands. Fine-tuning is the strategy of updating the weights of the pre-trained CNN's convolutional layers while planning the target dataset. This allows the show to alter its included representations to the specifics of the unused errand. The associated layers are initialized self-assertively and arranged from scratch. Fine-tuning the CNN on the target task routinely requires fewer planning cycles and less data than planning a total organizer from scratch. This makes it a commonsense and viable approach.

F. VGGFace Transfer Learning

VGGFace could be an unmistakable application of exchange learning within the field of confronting acknowledgment. It leverages the information and bits of knowledge picked up from the VGG (Visual Geometry Bunch) organize engineering, which was at first outlined for picture classification, and applies it to the space of confront acknowledgment. VGGFace exchange learning has demonstrated to be exceedingly compelling in recognizing and confirming faces, advertising state of-the-art execution in this basic space. The VGG organization, created by the Visual Geometry Bunch at the College of Oxford, is known for its profound engineering, which comprises 16 to 19 weight layers. These layers are convolutional and completely associated, making VGG a profound and effective neural organization. Initially planned for picture classification tasks, the VGG organize accomplished great results on benchmark datasets, which may be a confirmation of its capacity to capture and get complex visual highlights in pictures. Confront acknowledgment assignments require the extraction of particular facial highlights and designs. VGGFace exchange learning takes the pre-trained VGG to organize, and expel its classification layers and adjusts it for confront acknowledgment. By fine-tuning the VGG arrangement on face-related information, it can learn to extricate pertinent facial highlights, such as eyes, noses, and mouths. The arrangement generalizes these highlights and gets to be competent in recognizing individuals based on their facial characteristics.

VGGFace transfer learning offers a few preferences for confront acknowledgment: a. Include Extraction: The VGG organizer has as of now learned a wealthy set of highlights from a differing run of pictures. These highlights are profitable for recognizing facial qualities and personality. b. Vigor: VGGFace exchange learning upgrades the strength of confront acknowledgment frameworks to varieties in posture, lighting conditions, and facial expressions. c. Diminishment in Information Necessities: Rather than preparing a confront recognition model from scratch, which needs a broad dataset of labeled faces, VGGFace leverages pre-trained information. This diminishes the information necessities for the target assignment. VGGFace exchange learning has been broadly connected to different real-world applications, counting get-to get-to-control frameworks, surveillance, biometric authentication, and human-computer interaction. It is moreover important in celebrity acknowledgment, feeling examination, and age estimation from facial pictures, among other utilized cases. While VGGFace exchange learning is profoundly compelling, selecting the correct engineering, fine-tuning procedure, and preparing information is significant for the ideal to come about. Guaranteeing that the target confront acknowledgment dataset is assorted, and agent of the expecting utilize case is essential for the victory of the exchange learning preparation. VGGFace exchange learning may be an effective method that illustrates the centrality of leveraging pre-trained models in confronting acknowledgment. By adopting the VGG organized for this particular assignment, it accomplishes state-of-the-art standards. It serves as a foundation for building exact and strong confront acknowledgment frameworks over different applications.

Motivation: The motivation for integrating attention mechanisms and transfer learning in criminal identification arises from critical challenges in video surveillance. To bolster security and safety, address the data explosion in video feeds, tackle real-world scene complexities, and minimize false alarms, the incorporation of these advanced techniques enhances the efficiency of criminal identification models, pushing the boundaries of law enforcement technology.

Contribution: This research presents the theoretical foundations of VGGFace transfer learning for face recognition and its practical implementation, including the fine-tuning process and model evaluation. Research highlights the advantages, limitations, and potential challenges associated with this approach and provides insights into strategies for overcoming these challenges. The presented results demonstrate the superior performance of VGGFace transfer learning in comparison to traditional face recognition methods, emphasizing the significance of leveraging pre-trained deep learning models for face recognition tasks.

Organization: In the upcoming sections: Section 2 reviews related video surveillance work, Section 3 outlines our methodology, Section 4 presents experimental results and discussions, and Section 5 concludes the paper with key findings and future research directions.

II. RELATED WORK

Singla, S. & Chadha, R. [2] The review encompasses a comprehensive examination of prior research efforts, encompassing a spectrum of topics. It delves into the realms of object recognition and the identification of priority frames, exploring techniques and algorithms such as YOLO employed in the realm of crime detection. It also scrutinizes the diverse datasets utilized in conjunction with algorithms for crime data analysis and dataset training.

Sandhya et al., [3] have created an intelligent system for criminal detection and identification. This system harnesses the power of the OpenCV Deep Neural Network (DNN) model, utilizing a Single Shot Multibox Detector to identify faces.

Selvi et al., [4] introduced an innovative research project featuring the Enhanced Convolutional Neural Network (ECNN) for suspicious activity detection. The extensive experiment produced compelling results, meticulously analyzed through the use of the Statistical Package for the Social Sciences (SPSS) tool.

Kaiming et al., [5] introduced a novel residual learning framework for training deep neural networks. In this approach, the layers are explicitly reformulated as learning residual functions concerning the layer inputs, expressed as

$$F(x) = H(x) – x$$

where H(x) represents the stacked nonlinear layers. This formulation addresses the degradation problem associated with deep networks by making it easier to optimize the residual mapping compared to the original mapping. The authors showcase the effectiveness of this approach by achieving remarkable depths of up to 152 layers on the ImageNet dataset. The method is further evaluated on the CIFAR-10 dataset with 100 and 1000 layers, demonstrating its capability to handle increased network depth.

Manna et al., [6] introduces a face recognition system leveraging the FaceNet model for video-based face recognition. FaceNet is a pre-trained deep learning model designed for transforming face images into a compact Euclidean space. In this space, the distances between faces serve as a measure of their similarity.

Vaishali, B. et al., [7] present an effort to enhance the precision of criminal identification through the application of an Unsupervised Machine Learning Algorithm. The proposed model demonstrates a heightened accuracy of 92.46%, with a significance level of p¡0.05, in face detection compared to CNN classifiers, which exhibit an accuracy of 86%.

Venkatesh, Machala, et al., [8] proposed an automated facial recognition system using the Local Binary Patterns Histogram (LBPH) classifier and Fisher face algorithm, which utilizes a Haar feature-based cascade classifier to detect faces in real time, and the identified faces are then matched against a criminal database.

Al Sohan, Md Faruk Abdullah, et al., [9] presents a facial acknowledgment framework based on Convolutional Neural Systems (CNN) planned for programmed criminal recognizable proof. Preparing and testing utilize the Labeled Faces within the Wild (LFW) dataset, empowering the CNN powered framework to distinguish and analyze nitty gritty facial highlights. The show learns and recognizes one-of-a kind facial characteristics while preparing the LFW dataset. In this way, the prepared CNN is utilized to coordinate identified facial highlights with the history of criminal exercises, supporting the recognizable proof of potential suspects entering open areas.

Chambino et al., [10] introduces an inventive facial acknowledgment engineering that leverages numerous profound convolutional neural systems and multispectral pictures. A domain-specific transfer-learning approach is connected to a profound neural organize at first prepared on RGB pictures, illustrating viable generalization to the multispectral space. The incorporation of a skin locator module upgrades fraud discovery capabilities, especially within the nearness of confront veils and covers made from different materials. The domain specific transfer-learning parameters are fastidiously tuned, indicating which layers of the pre-trained organize ought to be retrained for ideal adjustment to multispectral pictures. The embeddings created by the prepared neural arrange are at that point utilized to survey the execution of bolster vector machines (SVM) and k-nearest neighbor classifiers. The proposed strategy experiences a comprehensive assessment against other state-of-the-art approaches, illustrating its predominant execution on the Tufts and CASIA NIR-VIS 2.0 multispectral databases with rank-1 scores coming to 99.7% and 99.8%, separately.

Ramgopal, M. et al., [11] introduce a solution that incorporates transfer learning and utilizes the YOLOv3 object detection model for the detection of both unmasked and masked faces. The selection of the YOLOv3 model is justified by its impressive performance metrics, boasting a rapid detection time of 0.012 s, an F1 score of 0.90, and a mAP score of 0.92, establishing it as an efficient and accurate choice for masked facial recognition. The proposed approach’s effectiveness is supported by experimental results on a Real-World Masked Face-Data set, demonstrating high recognition performance even in scenarios where facial features are partially obscured by masks.

Nikam et al., [13] develop a face detection and recognition system for criminal identification using a machine learning

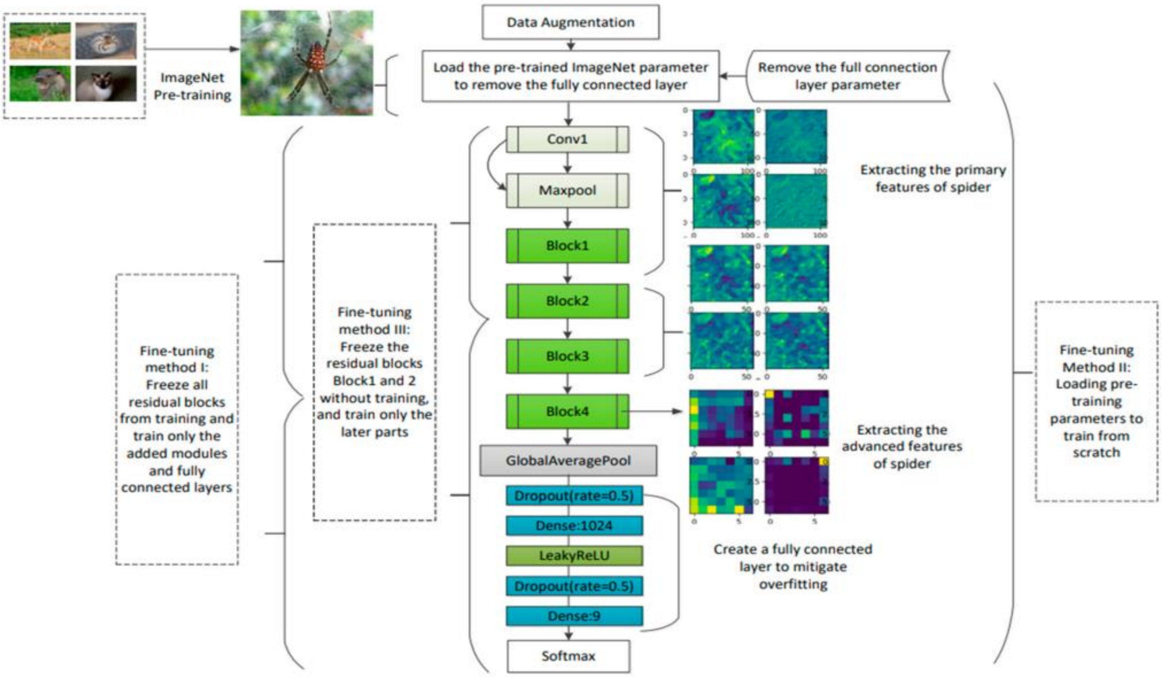

Fig. 1: Block Diagram of Proposed Attention-based VGG-16 Model

algorithm. This system employs a one-shot learning method, meaning it only requires a single image of the criminal for identification. To enhance performance and accuracy, Haar Cascade classifiers are utilized for object detection within the system. All relevant data, including criminal records, identification documents, and images, are stored in a SQLite database for comparison using the face recognition library. The primary objective of this application is to aid law enforcement agencies in locating criminals and providing essential information about tracked-down individuals.

Drakula [14] introduces an automated facial recognition system tailored for criminal databases, boasting an impressive matching rate of approximately 98%. It delves into the intricacies of face recognition within computer vision and its pivotal roles in security and surveillance domains. The system is meticulously structured around four key phases: database establishment, face detection, face recognition, and attendance management, all geared towards elevating accuracy and responsiveness in image-based face detection and recognition tasks.

Anitta et al., [15] centers on implementing an automated face recognition system geared towards identifying criminals or specific targets through a machine learning paradigm. The proposed approach harnesses Generative Adversarial Networks (GANs) to produce images of targets characterized by predefined feature sets for precise identification. Notably, the accuracy of the system is intricately linked to the number of training epochs within the network, yielding output images spanning from lower to higher quality. The method’s primary objective lies in discerning targets even amidst subtle variations in facial features, encompassing alterations such as hair color, eye color, and facial hair structure, thereby facilitating successful face recognition.

II. PROPOSED METHODOLOGY

The proposed method builds upon the utilization of the pre-trained deep learning model, VGG-16 (Visual Geometry Group) and incorporates an attention module for enhanced performance. VGG-16 model excels at extracting features at lower levels by using a smaller kernel size and has superior feature extraction capabilities.

The Attention-based VGG-16 comprises four key components: i) Attention module, ii) Convolution module, iii) Fully Connected (FC) layers, and iv) Softmax classifier as illustrated in Fig. 1.

The output feature map Y is calculated as given in Eq. (1). ReLU is the Rectified Linear Unit activation function.

$$Y(x,y,c) = \mathrm{ReLU}\left(\sum_{i=0}^{F-1}\sum_{j=0}^{F-1}\sum_{k=0}^{C-1} X(x+i,y+j,k)\cdot K(i,j,k) + b(c)\right) \quad (1)$$

Where:
• Y(x, y, c) represents the value at position (x, y, c) in the output feature map. x and y are the spatial coordinates in the output feature map. c is the index of the output channel.
• X(x+i, y+j, k) represents the value at position (x+i, y+j, k) in the input feature map.
• K(i, j, k) represents the weight at position (i, j, k) in the convolutional kernel.
• b(c) is the bias term associated with the output channel c.

IV. IMPLEMENTATION

Data Collection and Pre-processing: Collected Facial Recognition Dataset from Pinterest. The dataset consists of 68 faces each having 100 photos in the train folder and 20 photos of the same in the test folder. The preprocessing involved resizing the video frames from 128X128 pixels to 224X224 pixels.

Model Training: The model is trained using the annotated dataset, incorporating the attention mechanism for improved feature extraction. The loss function is calculated using the formula given in Eq. (2). Where yc is 1 if the true class is c and 0 for all other classes. yˆc is the predicted probability of class c.

$$E = -\sum_{c=1}^{C} y_c \log(\hat{y}_c) \quad (2)$$

Real-Time Processing: Developed a real-time video processing pipeline that captured frames from surveillance cameras, applied preprocessing, and fed frames into the model.

Culprit Identification: Utilized the attention mechanism to focus on relevant regions, identified features and compared them to a culprit database using similarity metrics.

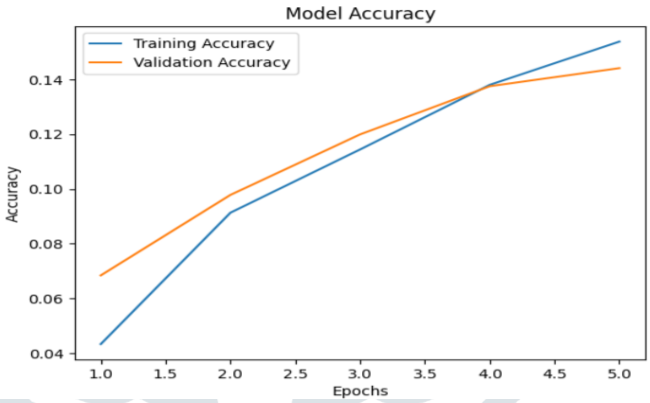

Fig. 2: Accuracy of the proposed model

V. RESULTS

The work demonstrated in [3] presents deep learning for both face detection and the identification of criminal suspects, but what sets the proposed model apart is the incorporation of an attention mechanism. This mechanism plays a pivotal role in identifying and extracting vital facial features from real time camera feeds, enhancing the ability to recognize criminals by assessing image similarities. The graphs Fig. 2 and Fig. 3 show the accuracy of the model and loss that occurred during the training. With the attention mechanism in place, the proposed model achieves improved feature extraction and representation, leading to notable enhancements in accuracy, precision, recall, and F1-Score, as demonstrated in the performance evaluation table.

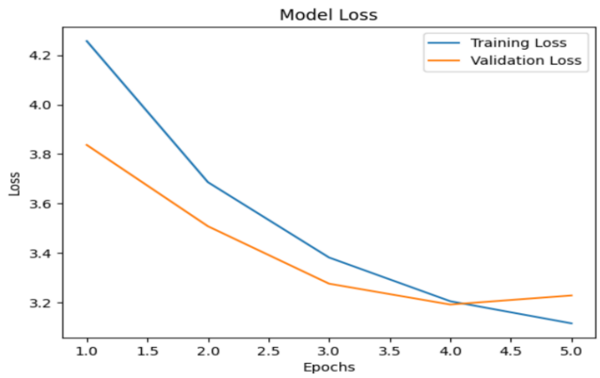

Fig. 3: Loss occurred during training

Table 1: Performance Evaluation

Model Configuration	Accuracy	Precision	Recall	F1-Score
Without AM [3]	0.85	0.88	0.82	0.85
Proposed Model	0.92	0.91	0.94	0.92
Improvement	+0.07	+0.03	+0.12	+0.07

VI. CONCLUSION

The proposed inquiry underscores the transformative effect of joining consideration components in real-time video observation for guilty party distinguishing proof. The integration of consideration components has been demonstrated instrumental in improving the exactness and productivity of the reconnaissance handle. The proposed work shows striking advancements in precision, accuracy, review, and F1 score, as proven by the results displayed in Table 1. By synergizing profound learning with consideration instruments, the investigation contributes to progressing offender distinguishing proof capabilities, setting the organization for more advanced security arrangements within the ever-evolving scene of observation innovation. Looking ahead, future investigative endeavors might investigate the synergies of consideration components and exchange learning inside the system of the CNN module. Such an integration holds a guarantee for tending to raise challenges and assist in refining real-time video reconnaissance, subsequently bracing its applications for the more prominent great of society.

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