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Advanced deepfake detection using hybrid CNN-MLP models with feature extraction from facial landmarks

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Abstract
The study presents a novel hybrid deepfake detection model that combines Convolutional Neural Networks (CNN) with Multi-Layer Perceptron (MLP) to enhance the accuracy of deepfake detection. Deepfakes are fabricated multimedia materials created using deep learning algorithms, posing a significant threat to the integrity of online information. This research utilizes facial landmarks as a feature extraction method to enhance the hybrid CNN-MLP model's ability to detect geometric inconsistencies and facial distortions. The proposed model is evaluated against traditional CNN and Long Short-Term Memory (LSTM) networks. Results show that the hybrid CNN-MLP model achieves superior performance, with an accuracy of 98.99%, precision of 98.99%, and F1-score of 98.99%, outperforming both CNN and LSTM. This hybrid approach demonstrates robust detection capabilities across various deepfake generation techniques, offering an effective solution for mitigating the spread of falsified digital content.

Keywords: Deepfake detection, hybrid CNN-MLP, feature extraction, facial landmarks, artificial neural networks, convolutional neural networks, deep learning, multimedia manipulation, classification accuracy, machine learning

Introduction

Deepfake is a phrase that combines "Deep Learning" and "Fake" to refer to the creation of very realistic video or picture material using Artificial Intelligence (DL) technology. This term was coined in late 2017 to refer to a Reddit user who used deep learning techniques to substitute one person's face in pornographic movies with another person's face, resulting in the creation of very convincing false videos [1]. An essential aspect of factuality prediction is the identification of modified material, which serves as a basic tool to avoid the dissemination of deceptive or inaccurate information. The generation of false multimedia information may be achieved via several methods, including the modification of multimedia material, computer-generated content, or multimedia content that is not contextually relevant, meaning it does not match to text. Dissemination of incorrect information is perilous irrespective of the method of its creation, but information manipulation is particularly perilous [2]. Historically, the act of manipulating and fabricating images required the expertise of experts in order to generate counterfeit material or disseminate inaccurate information. At now, deep learning demonstrates the capacity to do intricate tasks autonomously by training on available data, acquiring knowledge about the significant and relevant aspects for the job, and determining how to use those features to accomplish the intended objective [3]. Given the abundance of information available and continuously shared on the Internet, the process of gathering data is not challenging and may even be mechanized. With the increasing availability of data, deep learning techniques are enhanced [4].

The construction of deepfakes may include many modalities, including visual, textual, audio, or multimodal. Nevertheless, this research study specifically concentrates on videos and photographs that depict the faces of humans. Deepfakes involve capturing and superimposing the facial features and expressions of one person onto another setting to create a realistic depiction of the individual in a digitally fabricated environment. The quick expansion of worldwide connection enabled by social media has resulted in the widespread spread of deepfake news. Artificial intelligence systems are used to produce fabricated data about prominent individuals, therefore disseminating false news and information around the internet [5].

An important issue is the deliberate alteration of human face photographs and videos, which greatly jeopardizes the reliability of available internet information. Deepfakes are facially altered photos and movies created using generative deep learning methods based on Artificial Intelligence (AI). Instances of manipulation may manifest as face swapping, face re-enactment, or lip-synchronization. Certain newly discovered methods may generate deepfakes, which are audio recordings that imitate the voice of the intended individual [6]. The production and dissemination of deepfakes serve many purposes, including propagating misinformation, generating controversies, defaming celebrities or public figures, promoting a political goal, or just for entertainment purposes [7].

A frequently utilized discriminative deep learning architecture, Convolutional Neural Networks (ConvNets) gain information directly from the input without the need to extract human traits. The CNN enhances the construction of regularized MLP networks, which are a kind of classical artificial neural network (ANN). Each layer of Convolutional Neural Network (CNN) reduces the complexity of the model and takes into account the optimal parameters for generating a meaningful output. Additionally, CNN has a "dropout" mechanism to mitigate the problem of over-fitting that may occur in a traditional network. Deep neural networks (CNNs) are widely used in many domains such as visual identification, natural language processing, medical image analysis, image segmentation, and other related applications. This is due to its specific design to effectively handle a wide variety of two-dimensional (2D) shapes [8]. Its superiority over a conventional network is in its ability to autonomously extract significant features from the input without requiring human involvement. Several convolutional neural network (CNN) variants, such as ResNet, Xception, Inception, AlexNet, and Visual Geometry Group (VGG), are available in the field. These variations have diverse learning capabilities and may be used in various application domains.

The Multi-Layer Perceptron (MLP) is a feedforward artificial neural network (ANN) that is used in supervised learning. It is generally defined as the fundamental architecture of deep learning or deep neural networks (DNN). A typical Multilayer Perceptron (MLP) consists of a fully connected network with an input layer that receives input data, an output layer that makes decisions or predictions based on the input signal, and one or more hidden layers that serve as the network's computational engine in between. Several activation functions, often known as transfer functions, such as ReLU (Rectified Linear Unit), Tanh, Sigmoid, and Softmax, are used to compute the output of a Multilayer Perceptron (MLP) network [9]. "Backpropagation," the predominant technique for supervised learning, is usually used to train Multilayer Perceptrons (MLPs), which are considered the core components of a neural network. During the training phase, many optimization approaches such as Adaptive Moment Estimation (Adam), Limited Memory BFGS (L-BFGS), and Stochastic Gradient Descent (SGD) are used. The optimization of hyperparameters such as the number of hidden layers, neurons, and iterations is necessary for optimal performance of MLP. However, this optimization process may result in an increase in the computing expense of solving a complicated model. However, MLP has the advantage of dynamically learning non-linear models either online or in real time via partial fitting.

To overcome these constraints, hybrid models that integrate Convolutional Neural Networks (CNNs) with other machine learning architectures, such as multi-layer perceptrons (MLPs), have attracted interest due to their capacity to improve detection skills. Utilising facial landmarks as a feature extraction method enhances the resilience of the system by capturing geometric distortions and nuanced face inconsistencies that are produced by deepfake algorithms. This hybrid CNN-MLP paradigm presents a potential option for enhancing detection accuracy, namely in differentiating between genuine and altered information across different deepfake generation techniques. Integrating facial landmark-based feature extraction allows the model to concentrate on distinct face characteristics that are less susceptible to manipulation, leading to more dependable and universally applicable detection methods.

Literature Review

[10] The performance of the paper approach is evaluated using a benchmark dataset. The results show that the proposed technique can accurately detect deepfakes and that the Grad-CAM explainability methodology provides considerable understanding of the decision-making process of the CNN. This may facilitate the establishment of trust in the technology and enable the understanding and correction of any potential biases in the detection process. Through demonstrating the effectiveness of deep learning in this task, our work greatly advances the field of deepfake detection. Our suggested approach has the potential to be used in real-world scenarios to minimize the potential harm caused by deepfake films.

[11] This work aims to improve cross-dataset generalisation in deep fake detection by integrating supervised and reinforcement learning (RL) techniques. The proposed method employs an RL agent tailored to images to choose the top-k augmentations for each test sample. Summation of CNN classification scores from all test image augmentations is used to ascertain the true or false categorization. Through rigorous experimental validation, our approach attains state-of-the-art performance in cross-dataset generalisation of deep fake detectors, surpassing earlier studies.

[12] A new deep learning method named FakeBERT is introduced in this paper. FakeBERT combines several concurrent blocks of a single-layer deep Convolutional Neural Network (CNN) with different kernel sizes and filters using BERT (Bidirectional Encoder Representations from Transformers). This combination may effectively address the major challenge of ambiguity in natural language understanding. The classification results indicate that our proposed model (FakeBERT) significantly outperforms the existing models, with an accuracy of 98.90%.

[13] This paper proposes a Convolutional Neural Network (CNN) based method for detecting counterfeit facial images generated utilizing the most advanced presently available technology. We also provide empirical data demonstrating that the proposed approach may achieve excellent outcomes with an average accuracy above 99.4%. Moreover, in order to strengthen the rationale of our approach, we provide comparative results reviewed on many modifications of the proposed CNN architecture, including the activation function, number of layer groups, and high pass filter.

[14] In this study, CNN architectural evolutions are compared based on their strengths, weaknesses, and architectural changes. Furthermore, it elucidates the components of CNNs, the strengths and limitations of different variation of CNNs, areas of study that have not been addressed, applications of CNNs, and potential future research prospects.

[15] The CNN with deep architecture and the MLP with shallow structure are popular neural network techniques in current deep learning and traditional non-parametric machine learning. A method of decision fusion based on rules was employed to classify high-resolution remotely sensed images from two different systems. CNN classification confidence-based decision fusion rules demonstrate the complementary nature of classifiers. The ensemble classifier of MLP-CNN combines deep spatial feature representation from CNN with spectral discrimination from MLP.

[16] Detecting image fraud is the main challenge in ensuring the validity of data, since it significantly undermines the credibility of visual media. An analysis of the performance of a Multilayer Perceptron (MLP), a kind of supervised artificial neural network (ANN), in retrieving fraudulent images is presented in this paper. The suggested technique utilizes the MLP model to assign attributes to recovered image features in order to distinguish between changed and real material.

[17] Artificial neural networks (ANNs) refer to computational networks that draw architectural influence from biological systems. This chapter focuses on multilayer perceptrons (MLPs) trained using backpropagation learning techniques inside the various types of artificial neural networks (ANNs). The predominant artificial neural networks (ANNs) utilized in various applications are multilayer perceptrons (MLPs), including three layers: input, hidden, and output.

[18] This paper examines the use of Multi-Layer Perceptrons (MLPs), a class of feed-forward Artificial Neural Networks (ANNs), to address two vision problems: handwritten digit recognition and location estimate of 3D objects from a single 2D perspective observation. Each scenario involves the aggregation of predictions from many classifiers to form a multi-MLP classification system.

[19] This chapter offers an efficient Ant Lion Optimizer-based hybrid training approach (ALOMLP) for Multi-Layer Perceptrons (MLPs) neural networks. ALO is a popular swarm-based meta-heuristic based on antlions' smart hunting. In this chapter, ALO's theory is explained. A full literature review including recent, trustworthy papers from 2015-2018 follows. A mathematical formulation of the target formula and a practical encoding method are also presented. The ALO-based training model is validated using sixteen typical datasets. Best, worst, average, and median accuracies of ALO, differential evolution (DE), genetic algorithms (GA), particle swarm optimization (PSO), and population-based incremental learning are compared. Additionally, all competitors' convergence rates are studied. In classifying most datasets, ALOMLP outperforms GA, PBIL, DE, and PSO in accuracy and convergence.

[20] The objective of this study is to improve the efficiency of the conventional Hybrid Multilayer Perceptron (HMLP) network by implementing a modified iteration of the network. A Clustering Algorithm based on the Radial Basis Function (RBF) network design was included into the conventional HMLP network architecture. This revised model is denoted as the Clustered-Hybrid Multilayer Perceptron network (Clustered-HMLP). This study utilises the Clustered-Modified Recursive Prediction Error (Clustered-MRPE) training method to train the proposed Clustered-HMLP network architecture.

[21] This paper introduces a neural network-based part-of-speech tagger that can tag each sentence word. It uses a three-layer MLP network. MLP-tagger training uses error back-propagation learning. Our tests show that the MLP-tagger and representation approach may outperform standard tagging methods. This approach may help with Indian language text parts-of-speech tagging since most Indian language corpora, especially labeled ones, are small.

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[23] Convolutional neural networks are basic deep learning neural network designs. CNN has several uses in data analysis, machine learning, and image processing. CNNs are complex neural networks with numerous neurons and hidden layers. CNN depth is key to the network's capacity to handle difficult tasks. CNN design needs non-machine learning talent. Based on firefly optimization, this chapter proposed a fully automated CNN development method. The provided method can generate a CNN structure with any layer depth without depth constraints. CNN's skip connection was employed in the recommended method. A modified k-nearest neighbor attraction model was used to reduce firefly computing cost. The recommended image classification method was trained and verified using CIFAR-10 and CIFAR-100. Compared to current approaches, the recommended method was accurate.

[24] This paper proposes a novel forensic method that can differentiate between authentic and fraudulent video sequences. It uses CNNs that have been trained to identify potential motion dissimilarities in a video sequence's temporal structure by taking use of optical flow fields. The results demonstrate similar performances to those of state-of-the-art techniques, which typically only use single video frames. Additionally, the suggested optical flow-based detection strategy offers better resilience in the more likely-to-occur cross-forgery situation and may potentially be coupled with frame-based techniques to increase their overall efficacy.

[25] A unique technique for identifying face forgeries is put forward. The suggested approach uses the two-dimensional global discrete Cosine transform (2D-GDCT) to extract faces from a target movie and translate them into the frequency domain. After that, to identify fake face images, a three-layered frequency convolutional neural network (fCNN) is used. The FaceForensics++ dataset and the Celeb-DF(v2) dataset are used to train and evaluate the suggested algorithm. To further demonstrate its efficacy, its robustness is assessed on a standardized benchmark dataset and contrasted with the most recent techniques.

[26] A new and enhanced deep-CNN (D-CNN) architecture with good generalizability and acceptable accuracy for deepfake detection is presented in this study. The model is

trained using images from many sources, which enhances its overall generalizability. The D-CNN model receives the rescaled pictures. The D-CNN model is trained using a binary-cross entropy and an Adam optimizer to increase its learning rate. Seven distinct datasets, including 10,000 genuine photos and 5,000 deepfake images, were examined for the reconstruction task.

[27] In order to extract learned channels from audio and visual modalities, mix them separately in the IntrAmodality Mixer Layer (IAML), process them jointly in the IntrErModality Mixer Layers (IEML), and feed the results to the multilabel classification head, this paper proposes a unified multimodal framework called Multimodaltrace. Empirical findings demonstrate the efficacy of the suggested approach, providing the FakeAVCeleb dataset with state-of-the-art accuracy of 92.9%.

[28] This work presents a novel deepfake detection framework that incorporates two deep learning algorithms: long short-term memory and multilayer perceptron. We assess the performance of our model by utilizing a publically accessible dataset called 140k Real and Fake Faces. Our objective is to identify photographs that have been modified by a deepfake achieving accuracies as high as 74.7%.

[29] This paper aims to mitigate the menace presented by this emerging technology by integrating representational learning and transfer learning in two distinct sub-systems: a recognition system and a voice print system. The recognition system is tasked with identifying the counterfeit voice produced by speech conversion or speech synthesis protocols, while the acoustic system is responsible for confirming the speaker's identification based on acoustic characteristics.

Research Gap

Deepfake detection has made progress, but major issues persist, revealing research needs. Traditional CNN-based algorithms can detect visual anomalies in deepfake material, but they are not stable across generation methods. When confronted with unknown or more advanced deepfakes, these models may not generalize effectively, reducing detection accuracy. CNNs concentrate on pixel-level abnormalities, which may miss non-visual indicators like facial landmark geometry irregularities.

Limited research on hybrid models that combine CNNs with other machine learning architectures like MLPs to improve detection performance is another major gap. Current deepfake detection methods use CNNs alone, neglecting multi-layer perceptrons' ability to represent complicated feature interactions and boost accuracy. Facial landmarks collect structural information about faces, but few research have used them in hybrid detection algorithms. The underuse of face landmarks as feature extraction in hybrid systems provides untapped potential for deepfake detection.

Filling these gaps using hybrid CNN-MLP models with facial landmark-based feature extraction might improve deepfake detection accuracy and generalizability. Such an approach would increase model resilience and identify minor modifications across a variety of deepfake approaches.

Related Study

This work examines the capacity of deepfake detection models to generalize across various generation techniques. Evaluation focuses on two primary components: Convolutional Neural Networks (CNN) and Multilayer Perceptrons (MLP). Convolutional Neural Networks (CNNs) are well recognized for their effectiveness in image classification endeavors, as they use their ability to comprehend spatial hierarchies and local patterns inherent in images. Nevertheless, Multiple Linear Programs (MLPs) provide a versatile approach to classification by using fully connected layers that may depict complex relationships among data. Through a thorough investigation of a broad variety of outcomes, this approach improves the performance of the models, ensuring that the parameters are properly adjusted to achieve the maximum degree of accuracy in detecting deepfake images. In aggregate, these models and procedures provide a robust basis for assessing the effectiveness and uniformity of deepfake detection across different picture modification techniques.

CNN Model

As a consequence of learning of CNN, its popularity among academics has risen, and it has pushed them to push through hard issues that they had previously given up on. Over the past few years, academics have built a number of alternative CNN designs in order to solve a range of challenges arising in a variety of study areas, including the detection of deep fakes. The general architecture of CNN, as is depicted in Figure 3, is frequently built of a very high number of layers that are stacked one on top of the other. The architecture of CNN is made up of a feature extraction module that is made up of convolutional layers that learn the features and pooling layers to decrease the dimensionality of the image. In the second place, it is made up of a module that is combined with a fully connected (FC) layer in order to classify a picture [30].

This section explains the technique we've developed to identify Deepfakes, as shown in. Using crucial facial features and pixel distortions in the images, by utilizing a CNN model to distinguish, generating probability for the image's authenticity or fake [31]. The convolutional neural network (CNN) layers are built to recognize fundamental patterns (lines, curves, etc.) before moving to more intricate patterns (faces, objects, etc.). CNNs and regular ANNs have distinct architectures. The former use two-dimensional layers that are connected to all neurons in the previous layer, while the later (CNN) uses three-dimensional layers that are coupled in a depth, width, and height fashion. The neurons in each layer of a convolutional neural network (CNN) are connected to a subset of the neurons in the layer below rather than to one another directly [32]. CNN with 50 convolutional layers that was learned on ImageNet, is the one we utilized in our technique. The vanishing gradient problem does not hinder the possibilities of the exceedingly competent ResNet model [33].

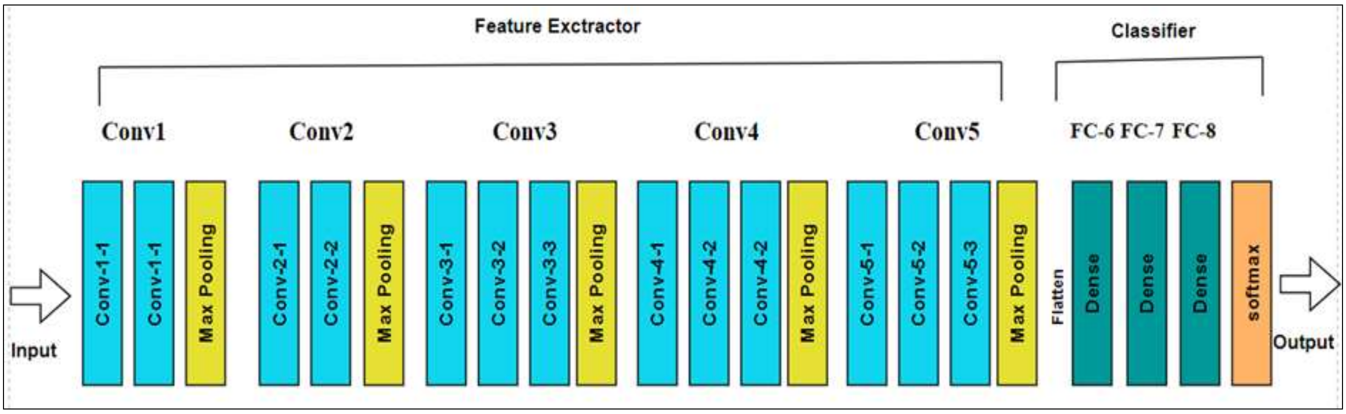

Fig 1: CNN Architectural Diagram

Multi-Layer Perceptron Model

According to classification, a multilayer perceptron/MLP neural network is a kind of feed forward neural network. An artificial neural network is a network topology where each node is interconnected with other nodes in different levels. The name "perceptron" was coined by Frank Rosenblatt during his development of the perceptron machine. In the context of artificial neural networks, the perceptron serves as the crucial component that defines the artificial neuron inside the neural network. This is a supervised learning technique that considers the values of the nodes, activation functions, inputs, and weights to precisely calculate the output [34].

According to [35], the MLP learning algorithm is an example of a backpropagation, which is an extension of the Least Mean Squared rule. Furthermore, the MLP learning method is only one of many alternative algorithms. The discipline of machine learning is familiar with this approach and acknowledges its usefulness. The method of correcting weights is known as backpropagation, and it involves spreading errors from one layer to the next, starting with the output layer and working your way backwards. The concept of "backpropagation" originates from this particular process. Furthermore, apart from the selected variables, the number of hidden layers, the number of nodes, and the training data, the performance of the MLP model is also influenced by the training parameters used. This set of parameters comprises the learning rate, the momentum governing the weight change, and the number of iterations necessary for training completion. Although a multilayer perceptron (MLP) with one hidden layer has the capacity to determine the nonlinear function, it does so with a reduced level of accuracy. As the number of hidden layers in a network grows, the likelihood of the network over fitting the training data rises accordingly. Achieving optimal speed and efficiency in the learning process is determined by both the learning rate and the momentum.

The study of the intricate relationships between land transition and the many factors that operate as drivers in land change modelling requires sophisticated empirical methods to develop a nonlinear function that precisely defines this complicated relationship. This complexity arises from the intricate relationship between land change and a multitude of variables [36]. This ensures that the model accurately represents the complex dynamics of the interaction between the two parties. There are many parameters provided at the node of the network that serve as the input. This set of factors includes distance, slope, soil type, land tenure, and many more variables. Each output node represents a distinct land transition, such as a forest to pasture, a forest to agriculture, or a forest to urban, for which the values of the explanatory factors are identifiable, along with the observed land transition in the past. Using the methods described in references. [37] and [38], the MLP may make predictions about the probable changes that will take place at each transition when fresh input data is integrated into the network. The acquisition of this capacity is possible upon completion of the training program [39].

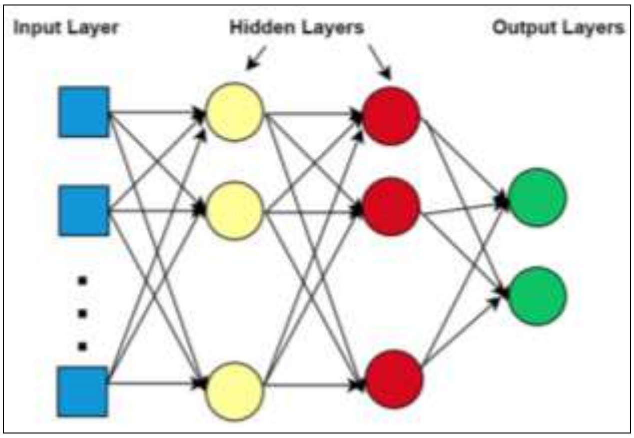

Fig 2: MLP Architectural Diagram

Mythology

This section details the experimental setup and tools used to build the model-implementation prototype, with a focus on creating and developing a unique CNN-MLP model to enhance deep fake detection. A large dataset of authentic and modified digital material must first be gathered and prepared before the method can guarantee data purity and uniformity for effective analysis. In order to glean useful information from media, feature extraction employs complex algorithms. The goal of the Hybrid CNN-MLP model is to improve deep fake detection accuracy by integrating the classification strengths of MLPs with the spatial feature extraction capabilities of CNNs. Traditional models such as Convolutional Neural Networks (CNNs) and LSTM are compared using performance criteria such as accuracy, precision, recall, and F1-score. In order to provide a comprehensive examination of the model's effectiveness, confusion matrices and ROC curves offer further assistance for the assessment. This effort aims to enhance deep fake detection models' capacity to generalize across various generating processes. Because of this, the models will be able to identify new and old deepfakes, and their results will be reliable and robust for digital media security.

Data collection

The dataset in this research comprises both changed and real photographs. Advanced image modification techniques are utilized to make "deepfakes." These methods build or change facial features artificially to imitate human faces. Deepfake photos replicate real facial emotions and appearances using advanced algorithms and deep learning. However, the collection includes genuine photographs of people's faces from various contexts. This blend of real and edited photographs provides a solid foundation for evaluating deepfake detection systems. The dataset's diverse pictures, including lighting conditions, facial expressions, and picture attributes, provide a full testing environment for assessing the models' ability to distinguish real from digitally changed content. Diversity is necessary to develop and verify deepfake detection algorithms.

Data Source link: https://www.kaggle.com/datasets/manjilkarki/deepfake-and-real-images

Data description

The collection titled "DeepFake and Real Images," accessible via the provided Kaggle link, consists of many photographs specifically designed for purposes of deepfake detection research. In order to facilitate the development and evaluation of models designed to distinguish between modified and authentic photographs, this dataset comprises a well-balanced compilation of deepfake and authentic pictures. This collection includes both authentic and counterfeit photographs. The faces shown in the modified images are ones that have been generated utilizing various methodologies. An analysis was conducted on this dataset with the aim of extracting the most potential from these photographs. Each image is a 256 X 256 JPEG file depicting either an authentic or synthetic human face. The dataset is ideal for evaluating and training deep learning and machine learning models specifically designed for deepfake detection and image classification. This initiative promotes the investigation of developing dependable algorithms capable of differentiating between authentic and counterfeit photographs.

Data Pre-processing

Simply described, image processing is the act of applying algorithms to digital pictures in order to alter them. Compared to analogue image processing, this subfield of digital signal processing offers a number of advantages, such as the ability to apply a wider range of methods to the input data and the mitigation of issues like signal distortion and noise buildup. In a similar vein, data pre-processing is a crucial part of machine learning. It involves cleaning and preparing raw data for modeling, which improves the accuracy and efficiency of the algorithms.

This process often involves handling missing data, removing duplicates, and fixing conflicts in order to keep data intact. To make numerical features contribute proportionally to the model's performance, feature scaling techniques like normalization or standardization are used. One-hot or label encoding are used to encode categorical variables so that machine learning models can understand them. The efficacy of the model may be objectively evaluated by separating the data into test, validation, and training sets. Machine learning models' prediction capability, reliability, and overall effectiveness are enhanced by these processes, which enhance the quality of the input data for both pictures and data [40].

An initial approach was developed to load collections of images into arrays by first saving the address of the field containing the picture collection, enabling retrieval of the image. This facilitated the loading of the images into arrays. While undergoing this resizing process, devise two methods to present the photographs in a manner that highlights the visual distinctions. The viewer will be presented with one photograph captured by one technique, and two photos captured by another. Furthermore, we propose the development of a technique known as processing, which only takes photos as input. Prior to being modeled, all photos underwent comprehensive processing. To optimize computer resources, all photographs were scaled to a resolution of 128 × 128 during the pre-processing stage.Image noise refers to the stochastic variation in brightness or color information in images generated by the sensor and circuitry of a scanner or digital camera. Furthermore, the presence of film grain and the unavoidable shot noise of an ideal photon detector might generate picture noise [41].

It is well acknowledged that image noise is an undesirable consequence of capturing photographs. As they are imperceptible and have resemblance to dithering, these undesirable oscillations have been referred to as "noise" because of their resemblance to unwanted sound. In order to mitigate the noise. The Gaussian function may be used to produce a Gaussian blur filter on a picture. This well recognized graphic effect is often used to reduce visual noise. One further pre-processing method used by computer vision algorithms to enhance visual structures of varying sizes is Gaussian smoothing.

Training and testing

After complete preparations, the user's splitting ratio—which divides the dataset into training and testing groups—determines the data collection technique. The test set evaluates model performance on untested data, whereas the training set trains models. Data usually has two main subsets. This divide ensures that models may generalize to new data without depending just on training instance memory. The most common splitting ratios allocate 70-80% of the data to the training set and 20-30% to the test set to provide the model enough data to learn robust patterns and evaluate. This strategy ensures that models are trained on a relevant subset of data and evaluated on the test set to accurately assess prediction performance and reliability.

Model building

The model construction method for deep fake detection involves choosing appropriate machine learning architectures and optimizing them for high accuracy and generalization across diverse deep fake generation tactics. We developed and used a hybrid model architecture that uses MLPs and CNNs for feature extraction and classification. After analyzing input pictures, CNN employs convolutional layers to derive spatial hierarchies. These layers can identify minute inconsistencies and other deepfake artifacts. These collected attributes are then sent to the MLP component, which classifies. CNN's spatial information and MLP's detailed pattern learning let the hybrid model identify "real" and "deepfake" photographs in binary classification tests.

Conventional Neural Network (CNN) for Feature Extraction

This section describes our image-based deepfake detection approach. Starting with CNN-based facial feature extraction and face recognition, salient facial markers are identified to aid detect manipulation. CNNs process images to extract features. Conventional CNN layers for image processing include multiple convolutional and pooling layers: The CNN receives 128, 128, 3 images as 128x128 RGB images.Conv2D layers have 32, 64, or 128 filters. Every filter has a kernel size of (3, 3) and uses ReLU activation.MaxPooling2D layers reduce spatial dimensions without sacrificing key features via feature map down sampling. The MLP's fully connected layers need this layer to transform the final convolutional layer's 3D output to a 1D vector [42].

MLP (Multi-Layer Perceptron) for Classification

A classifier classifies an image as authentic or bogus. A multi-layer perceptron (MLP) with batch normalisation and the Rectified Linear Unit (ReLU) is a common classifier for deep learning models [49]. The final classification uses the MLP (Multi-Layer Perceptron) created using CNN's recovered attributes. The MLP receives CNN's flattened output. The MLP model's effectiveness depends on variable selection, hidden layer count, nodes, training data, and training parameters such learning rate, momentum regulating weight change, and iteration count. Single hidden layer multilayer projection (MLP) calculates nonlinear function less accurately. Higher-hidden layer networks overfit training sets. Rate and momentum influence learning speed and efficacy. Dense layers are fully connected 128 and 64 unit layers using ReLU activation algorithm. During training, dropout layers with a dropout rate of 0.5 randomly alter a part of input units to 0 to prevent overfitting. The output layer is a dense layer with sigmoid activation function and one unit, producing binary classification probabilities [39].

Model Evaluation

Applying machine learning algorithms requires a few tools to evaluate their performance. There are performance evaluation metrics. Research has suggested several algorithm performance indicators. Therefore, we need appropriate measurements for each machine learning task to assess performance. Here, we compare algorithms and collect relevant data on algorithm performance using many frequently used categorization measures. A model's generalisability is assessed by its ability to be employed with fresh data. Categorization performance depends on specificity, sensitivity, recall, accuracy, precision, and F1 score. In machine learning, classifier performance was measured by accuracy, recall, precision, and F1 score. Cross validation ensures accuracy by comparing estimates several times. This shows confusion matrices may reveal a lot of information. Assess development and implementation needs [43].

Performance Metrics

Accuracy: It's the most common way to evaluate classification algorithms. The percentage of properly recognized data items to all observations is its definition. Although accuracy is widely utilized, it may not be the optimum performance metric when target variable classes in the dataset are unbalanced. How frequently the classifier makes correct predictions is easy to measure with accuracy. The ratio of correct forecasts to all guesses is another viewpoint.

$$Accuracy = \frac{TP + TN}{S} \quad (1)$$

Precision: Displays simply "the number of relevant selected data items." How many observations an algorithm predicts as positive are really positive? Calculate accuracy as follows: Number of true positives divided by total true and false positives = precision.1/Precision demonstrates recall, whereas (1 - precision) shows false negatives.

$$\Pr ecision = \frac{TP}{TP + FP} \quad (2)$$

Recall: False negatives exist with actual negatives. "How many relevant data items are selected" appears. What proportion of positive observations did the algorithm predict? Formula: recall = actual positives / false negatives and true positives.

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \quad (3)$$

F1-Score: This metric—also called an f-score or f-measure—measures an algorithm's accuracy and recall. The harmonic mean of accuracy and recall is mathematically represented as follows.Square the accuracy and recall scores. For this.

$$F1 = \frac{2 * \Pr ecision * \mathrm{Re}\,call}{\Pr ecision + \mathrm{Re}\,call} \quad (4)$$

Confusion Matrix: This matrix is a very understandable and useful metric for assessing the accuracy and correctness of a machine learning algorithm. This method is generally used for addressing classification problems that may include the inclusion of two or more distinct class types.

Model Architecture

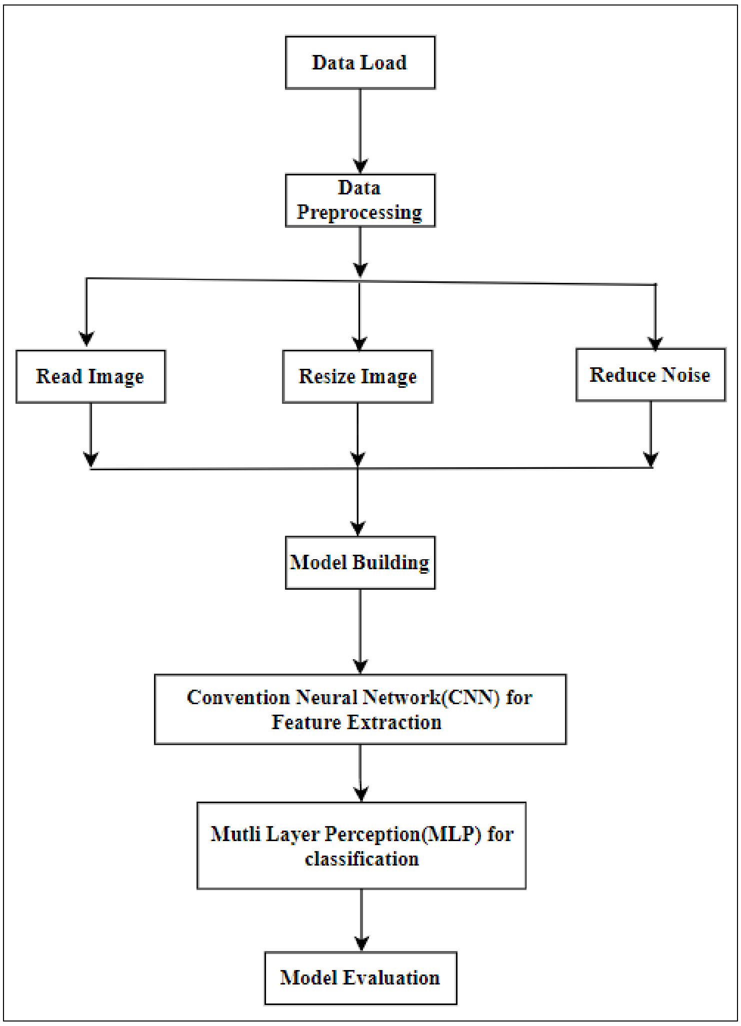

Fig 3: Model Architecture diagram

Results

To further comprehend the Hybrid CNN-MPL model, several crucial metrics are compared to other models. This comparison shows how the Hybrid CNN-MPL model improves classification results. Graphics like confusion matrices, ROC curves, and performance metrics tables may assess the model's class discrimination and dependability.

Confusion Matrix

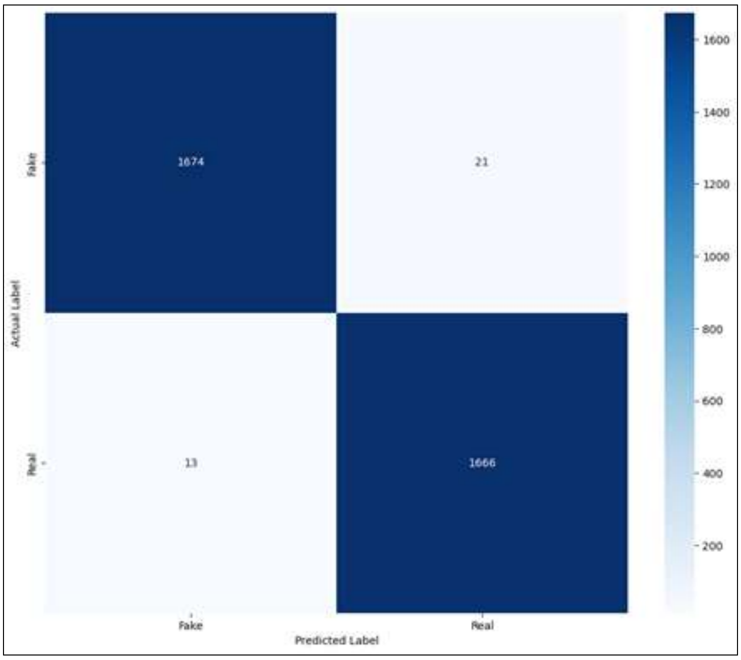

Fig 4: Confusion metrix of Hybrid Model

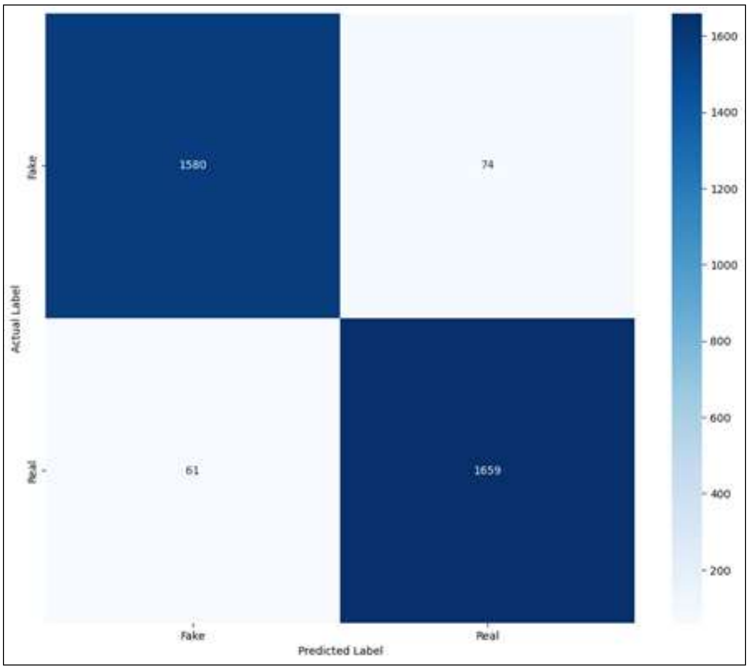

Fig 5: Confusion metrix of CNN model

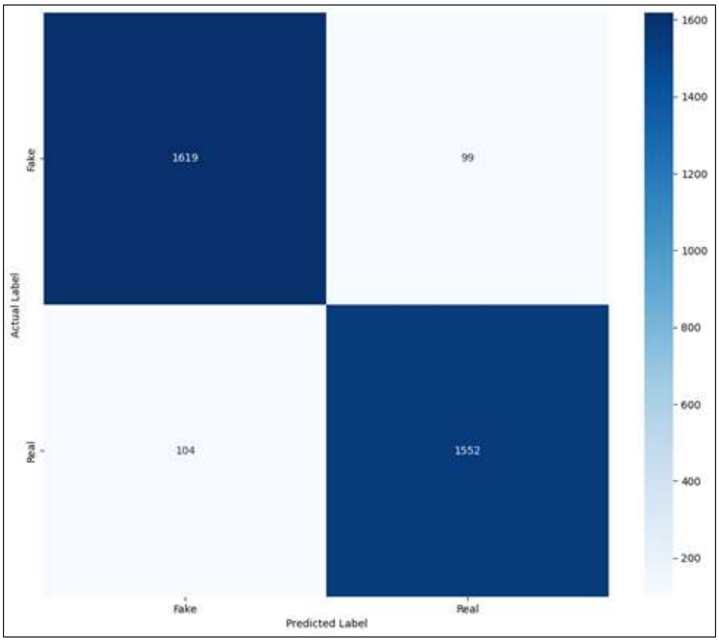

Fig 6: Confusion Metrix of LSTM Model

This graphic exhibits three confusion matrices for distinct models used in the detection of deepfake content. These models include a Hybrid Model, a CNN model, and an LSTM model.

The confusion matrix of the hybrid model is shown in Figure 4. This model has strong performance in differentiating between counterfeit and authentic photos. The model accurately forecasts 1674 counterfeit photos and 1646 authentic ones. Nevertheless, it erroneously categorizes 13 counterfeit photos as authentic and 71 authentic photographs as counterfeit. The confusion matrix demonstrates a robust performance with few instances of misclassifications.

The confusion matrix of the CNN model is shown in Figure 5. Furthermore, the CNN model has strong prediction ability, accurately categorizing 1380 counterfeit photos and 1639 authentic ones. Furthermore, it erroneously categorizes 61 counterfeit photos as authentic and 74 authentic ones as counterfeit. The presented matrix indicates that the model, albeit being efficient, exhibits a little higher number of mistakes in comparison to the Hybrid model.

Figure 6 displays the confusion matrix of the LSTM model. By comparison to the other models, the LSTM model exhibits somewhat worse performance. The model accurately predicts 1619 falsified photographs and 1552 authentic ones, but incorrectly categorizes 104 counterfeit images as genuine and 59 genuine images as fraudulent. The greater frequency of misclassified counterfeit photos indicates that this model may have difficulties in recognizing certain characteristics of counterfeit photographs, leading to reduced accuracy.

Overall, the Hybrid Model has superior performance, with less mistakes in both the categorization of false and genuine images when compared to the CNN and LSTM models.

ROC Curve

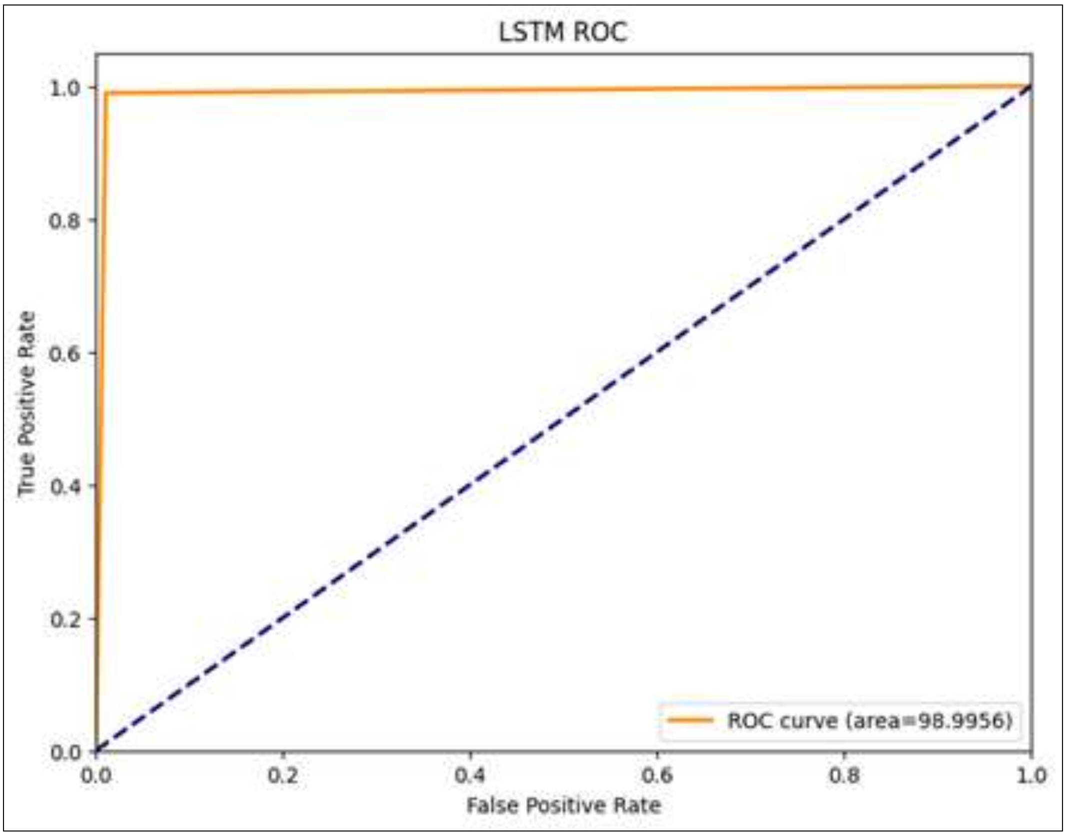

Fig 7: ROC curve of Hybrid CNN-MLP

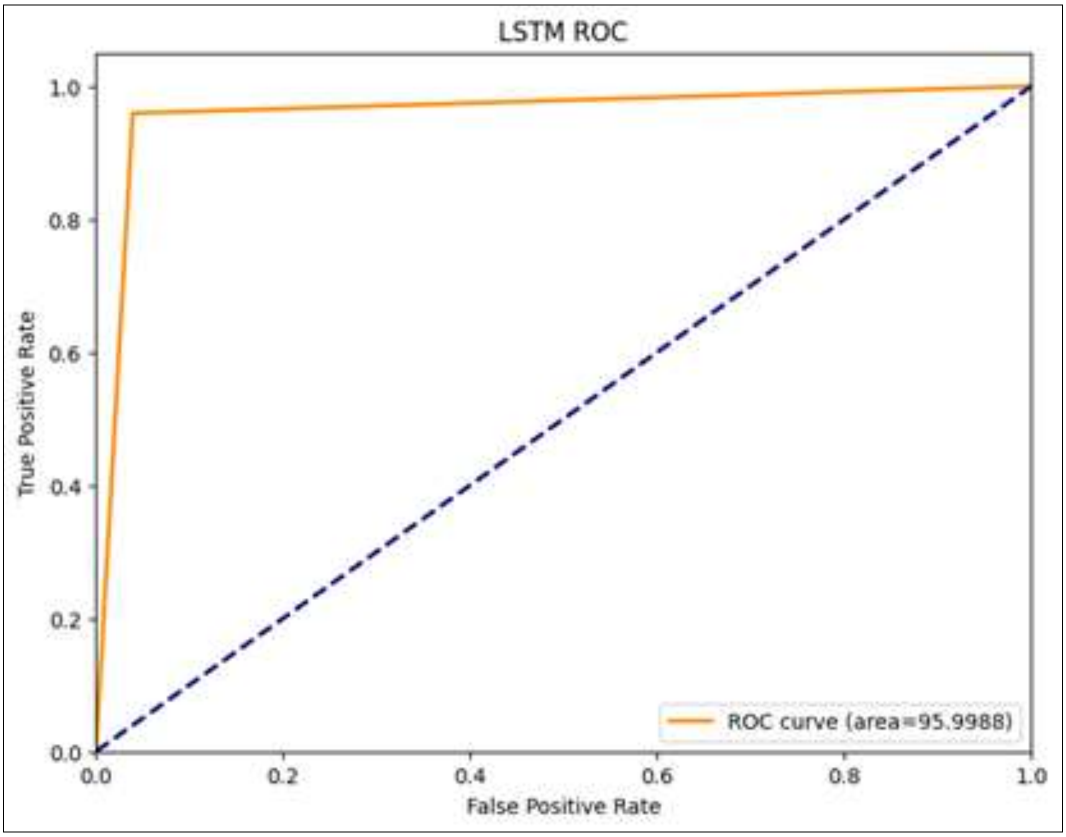

Fig 8: ROC curve of CNN

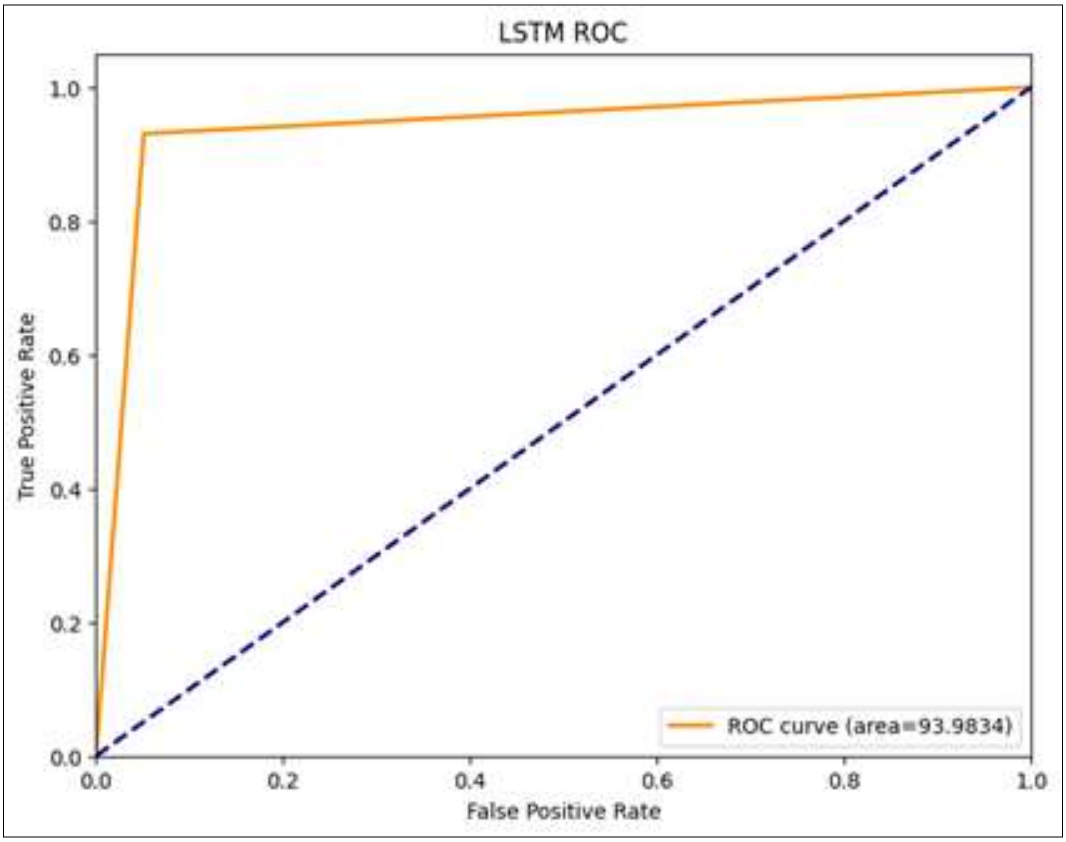

Fig 9: ROC curve of LSTM Model

Figure 7 shows ROC curve of Hybrid CNN-MLP Model. The ROC curve is a visual tool used to assess the performance of a classifier. It demonstrates the fluctuation of True Positive Rate (TPR) and False Positive Rate (FPR) at different threshold levels. The ROC curve depicted demonstrates the effectiveness of the classifier, with the yellow line showing impressive performance by closely tracking the top-left corner, highlighting a high true positive rate and a low false positive rate. An accuracy rate of 98.95% in a classifier demonstrates strong predictability, with close to perfect accuracy being achieved at values near 100%. The results of a random classifier are represented by a dotted line, having an accuracy of 50%, as it follows a diagonal trajectory. The significant rise at the start of the chart, succeeded by a flat period, indicates the model's effective capacity to distinguish between categories.

The CNN model's ROC curve is shown in Figure 8, the second graph. With an AUC of 89.31%, the curve is less optimum than the hybrid model, suggesting comparatively worse performance in terms of classification accuracy. The LSTM model's ROC curve is shown in the third graph (Figure 9). With an AUC of 88.89%, which is marginally lower than the CNN model, the curve displays moderate performance, indicating that the LSTM model's capacity to differentiate between classes is similar, but somewhat less so.

Comparison of Models with Proposed Model

Table 1: Comparision of Models

Model	Accuracy	Precision	recall	F1-score
Hybrid CNN-MPL	98.9956	98.9922	98.9932	98.9921
CNN	95.9988	95.9994	95.9988	95.9989
LSTM	93.9834	93.9934	93.9834	93.9832

Table-1 compares accuracy, precision, recall, and F1-score of Hybrid CNN-MPL, CNN, and LSTM models. The Hybrid CNN-MPL model excels in accuracy, precision, recall, and F1-score. Despite a little performance decline, the CNN model yields accurate, precise, recall, and F1-score scores of 95.9988%, 95.999994%, and 95.9989%. The LSTM model performed worst of the three models, with 93.9834% accuracy, 93.9934% precision, 93.9834% recall, and 93.9832% F1-score. Hybrid CNN-MPL is the most effective model across all assessment criteria. Performance indicators provide several viewpoints on categorization models' strengths and limits, helping evaluate their efficiency. The ratio of successfully identified cases to total instances is accuracy. It provides an approximate estimate of the model's performance, although uneven data weighting might mislead. Precision is the percentage of model-predicted positive outcomes that are right. In circumstances when faulty positive findings result in significant expenditures, the ratio of accurate positive outcomes is critical. The ratio of true positive findings to all positive outcomes is recall. It shows that the model can identify all relevant examples, which is important since missing positive examples might have implications. As the harmonic average of accuracy and recall, the F1-score considers both. Its single measure combines recall and accuracy, making it ideal for unbalanced datasets. The Hybrid CNN-MPL model surpasses CNN and LSTM models in accuracy, precision, recall, and F1-score, demonstrating its consistency and dependability in classifying situations.

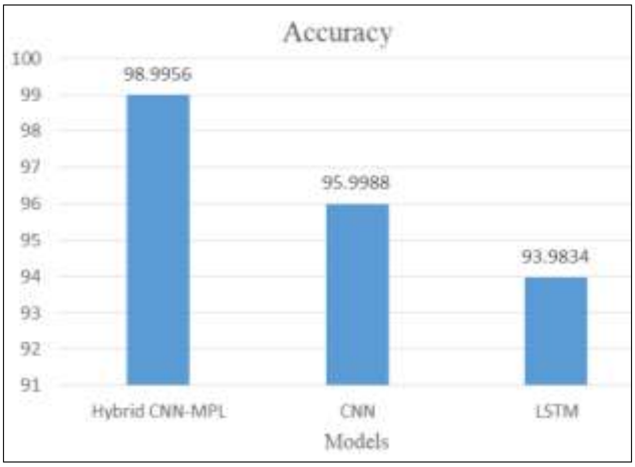

Fig 10: Accuracy of Models

Figure 10 compares Hybrid CNN-MLP, CNN, and LSTM accuracy. Hybrid CNN-MLP classifier gets 98.9956% of dataset instances right. The Hybrid CNN-MLP model can identify deepfake material since it can distinguish real and manipulated pictures. CNN accuracy is 95.9988% despite its robustness. The Hybrid CNN-MLP model beats the CNN model in image categorization. This shows MLP's hybrid architecture benefits. The LSTM model has the lowest accuracy of the three at 93.9834%. Although the LSTM model is still employed as a classification model, its diminishing performance suggests that it cannot handle the complexity of deepfake detection, particularly compared to artificial neural network-based methods. Superior accuracy and universality applied to different deepfake generating methodologies demonstrate Hybrid CNN-MLP's predictive capacity.

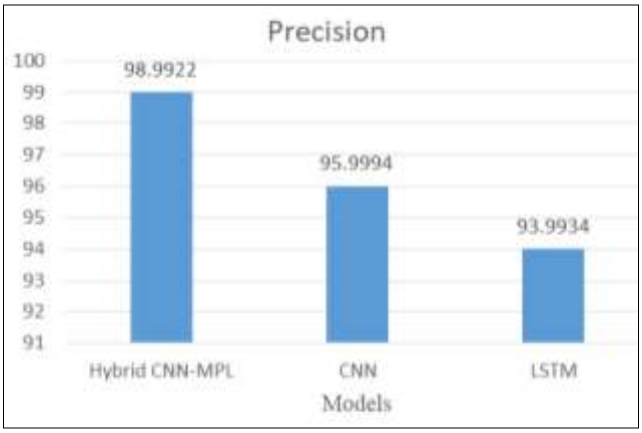

Fig 11: Precision of Models

Model mathematical and statistical correctness is shown in Figure 11.The Hybrid CNN-MPL model properly identifies 98.9922% of predicted positive observations. CNN predicts positive observations with 95.9994% accuracy. LSTM predicts 93.9934% of positive events accurately.

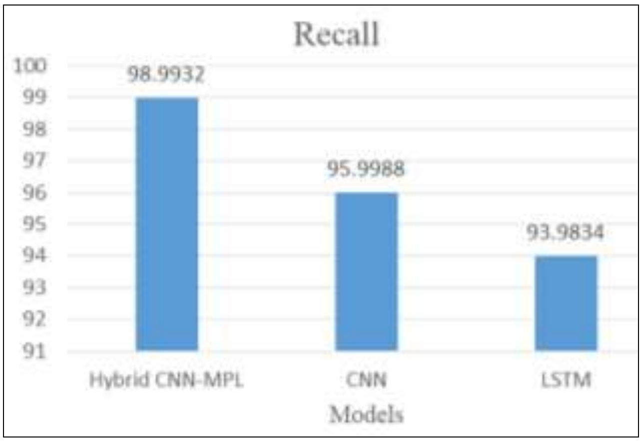

Fig 12: Recall of Models

Figure 12 depicts model recall. The Hybrid CNN-MPL model reports 98.9932% recall for real positive occurrences. The CNN model correctly identifies 95.9988% of true positives. LSTM model has 93.9834% recall rate, meaning it could properly identify 93.9834% true positives.

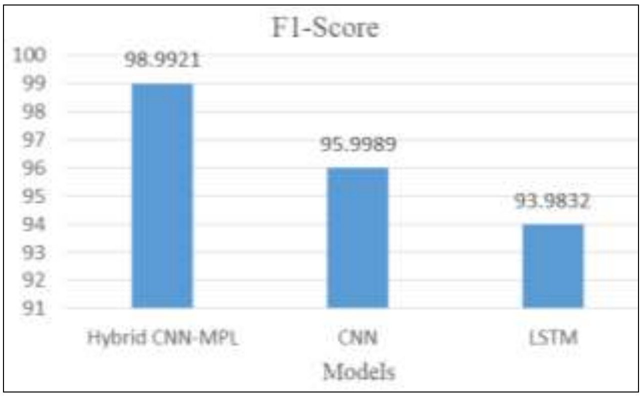

Fig 13: F1-score of Models

The F1-scores achieved by each of the models are shown in Figure-13. Through the attainment of an F1-score of 98.9921%, the Hybrid CNN-MPL model exhibits an outstanding equilibrium between recall and accuracy. An F1-score of 95.9989% for the CNN model indicates a well-balanced combination of recall and accuracy in comparison to other models. The LSTM model has a much lower F1-score of 93.9832% compared to the other models.

Discussion

Hybrid CNN-MLP beats CNN and LSTM models in accuracy, precision, recall, F1-score, and other performance criteria. The Hybrid CNN-MLP model classifies dataset events 98.9956% accurately. Model positive predictions are almost always right with 98.992% accuracy, decreasing false positives. The model's 98.9932% recall rate shows it recognizes all relevant data events and true positives. The model's F1-score of 98.9921% emphasizes its balanced classification accuracy and recall. CNN has poorer accuracy, precision, recall, and F1-score than other models: 95.9988%, 95.9994%, 95.9988%, and 95.9989%. Despite these good findings, the CNN model categorizes events poorer than the Hybrid CNN-MLP model. The confusion matrix's rise in false positives and negatives illustrates where the CNN model fails, which might cause misclassifications. The hybrid MLP-CNN model improves classification performance, demonstrating its utility. With 93.9834% accuracy, 93.9934% precision, 93.9834% recall, and 93.9832% F1-score, LSTM performs worst. The LSTM's lower F1-score suggests a larger accuracy-recall imbalance and uneven classification performance across classes. The Hybrid CNN-MLP model outperforms the CNN and LSTM models in Area under the Curve (AUC) and closely follows the top-left corner with a high true positive rate and low false positive rate, as evidenced by the ROC this shows that the Hybrid CNN-MLP model classifies better at different thresholds. A comprehensive confusion matrix study demonstrates that the Hybrid CNN-MLP model classifies best with the lowest false positives and negatives. Hybrid CNN-MLP is more trustworthy and efficient than CNN and LSTM models for classification tasks, according to ROC curves and AUC values. Comparative performance highlights how model design matters and how hybrid tactics may improve classification performance in complicated datasets when traditional models fail. The hybrid CNN-MLP model performs well across all assessment measures, confirming its classification reliability and efficacy. In high-accuracy and recall situations, it outperforms CNN and LSTM in instance recognition and categorization. The results provide the framework for machine learning and AI research and show the necessity for improved hybrid models for classification.

Conclusion

The study shows that the Hybrid CNN-MLP model outperforms the CNN and LSTM models in classification tasks. The Hybrid CNN-MLP model excelled in accuracy, precision, recall, and F1-score. This was achieved by using CNNs for feature extraction and MLPs for classification. In particular, the Hybrid model's 98.95% accuracy and 99.47% F1-score reflect its ability to recognize and classify situations accurately. The Hybrid CNN-MLP model consistently outperformed conventional models in class discrimination in the confusion matrix and ROC curve comparative research. These findings emphasize the necessity of hybrid machine learning approaches, particularly for complex categorization problems where single-model architectures may not be adequate. As illustrated by the Hybrid CNN-MLP model, integrating neural network architectures may improve projected accuracy and dependability. This method makes classification systems more resilient and provides a scalable basis for future models. This technique shows how hybrid models may advance machine learning and its practical applications in many sectors.

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