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ABSTRACT

The growing computation power has made the deep learning algorithms so powerful that creating a indistinguishable human synthesized video popularly called as deep fakes have become very simple. Scenarios where this realistic face swapped deep fakes are used to create political distress, fake terrorism events, revenge porn, blackmail peoples are easily envisioned. In this work, we describe a new deep learning-based method that can effectively distinguish AI-generated fake videos from real videos. Our method is capable of automatically detecting the replacement and reenactment deep fakes. We are trying to use Artificial Intelligence (AI) to fight Artificial Intelligence (AI). Our system uses a Res-Next Convolution neural network to extract the frame-level features and these features and further used to train the Long Short-Term Memory (LSTM) based Recurrent Neural Network (RNN) to classify whether the video is subject to any kind of manipulation or not, i.e whether the video is deep fake or real video. To emulate the real time scenarios and make the model perform better on real time data, we evaluate our method on large amount of balanced and mixed data-set prepared by mixing the various available data-set like Face-Forensic++[1], Deepfake detection challenge[2], and Celeb-DF[3]. We also show how our system can achieve competitive result using very simple and robust approach.

Problem Statement

Convincing manipulations of digital images and videos have been demonstrated for several decades through the use of visual effects, recent advances in deep learning have led to a dramatic increase in the realism of fake content and the accessibility in which it can be created. These so-called AI-synthesized media (popularly referred to as deep fakes). Creating the Deep Fakes using the Artificially intelligent tools are simple task. But, when it comes to detection of these Deep Fakes, it is major challenge. Already in the history there are many examples where the deepfakes are used as powerful way to create political tension [14], fake terrorism events, revenge porn, blackmail peoples etc. So, it becomes very important to detect these deepfake and avoid the percolation of deepfake through social media platforms. We have taken a step forward in detecting the deep fakes using LSTM based artificial Neural network.

Goal and Objectives

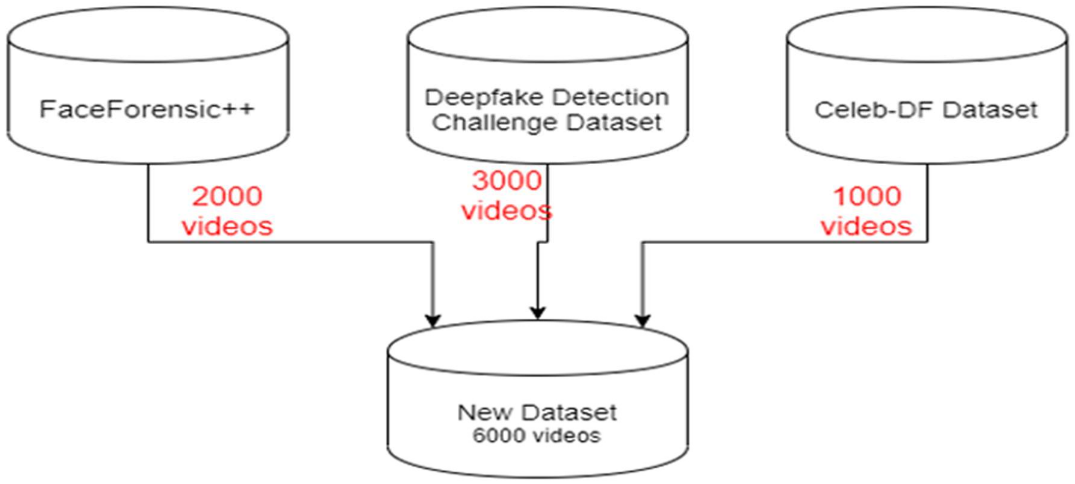
- Our project aims at discovering the distorted truth of the deep fakes.
- Our project will reduce the Abuses' and misleading of the common people on the world wide web.
- Our project will distinguish and classify the video as deepfake or pristine.
- Provide a easy to use system for used to upload the video and distinguish whether the video is real or fake.

Major Constraints

- **User:** User of the application will be able detect the whether the uploaded video is fake or real, along with the model confidence of the prediction.
- **Prediction:** The User will be able to see the playing video with the output on the face along with the confidence of the model.
- **Easy and User-friendly User-Interface:** Users seem to prefer a more simplified process of Deep Fake video detection. Hence, a straight forward and user-friendly interface is implemented. The UI contains a browse tab to select the video for processing. It reduces the complications and at the same time enrich the user experience.
- **Cross-platform compatibility:** with an ever-increasing target market, accessibility should be your main priority. By enabling a cross-platform compatibility feature, you can increase your reach to across different platforms. Being a server-side application, it will run on any device that has a web browser installed in it.

Module 1: Data-set Gathering

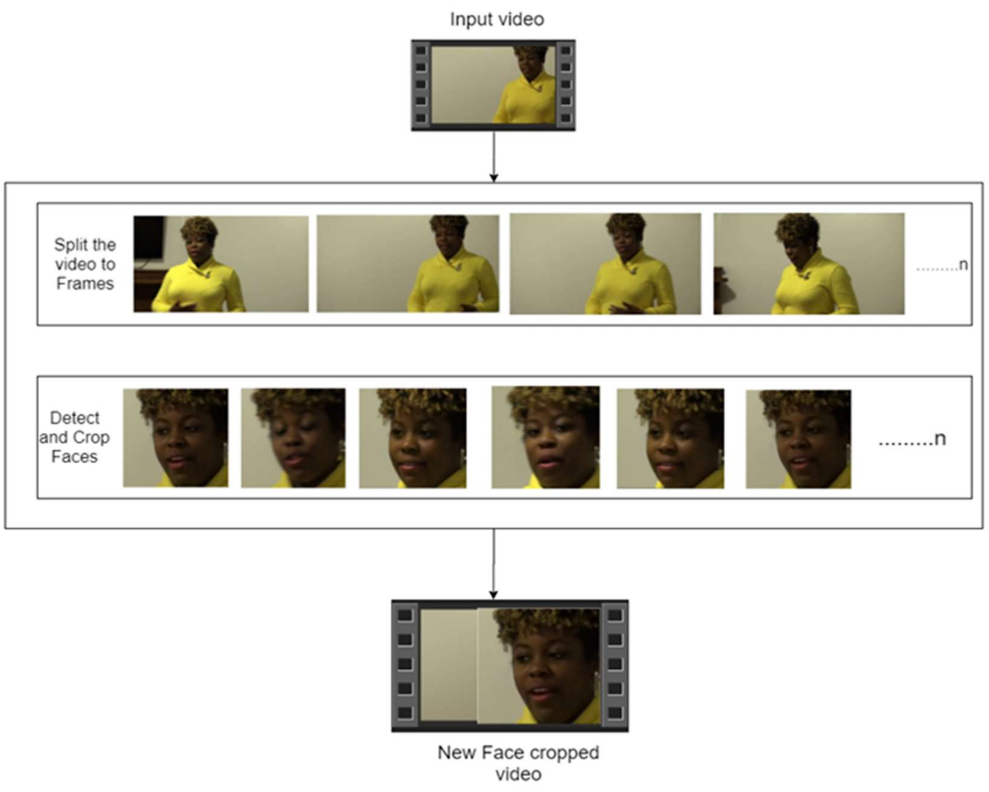
For making the model efficient for real time prediction. We have gathered the data from different available data-sets like FaceForensic++(FF)[1], Deepfake detection challenge(DFDC)[2], and Celeb-DF[3]. Further we have mixed the dataset the collected datasets and created our own new dataset, to accurate and real time detection on different kind of videos. To avoid the training bias of the model we have considered 50% Real and 50% fake videos. Deep fake detection challenge (DFDC) dataset [3] consist of certain audio alerted video, as audio deepfake are out of scope for this paper. We preprocessed the DFDC dataset and removed the audio altered videos from the dataset by running a python script. After preprocessing of the DFDC dataset, we have taken 1500 Real and 1500 Fake videos from the DFDC dataset. 1000 Real and 1000 Fake videos from the FaceForensic++(FF)[1] dataset and 500 Real and 500 Fake videos from the Celeb DF[3]dataset. Which makes our total dataset consisting 3000 Real, 3000 fake videos and 6000 videos in total. Figure 2 depicts the distribution of the data-sets.



Module 2: Pre-processing

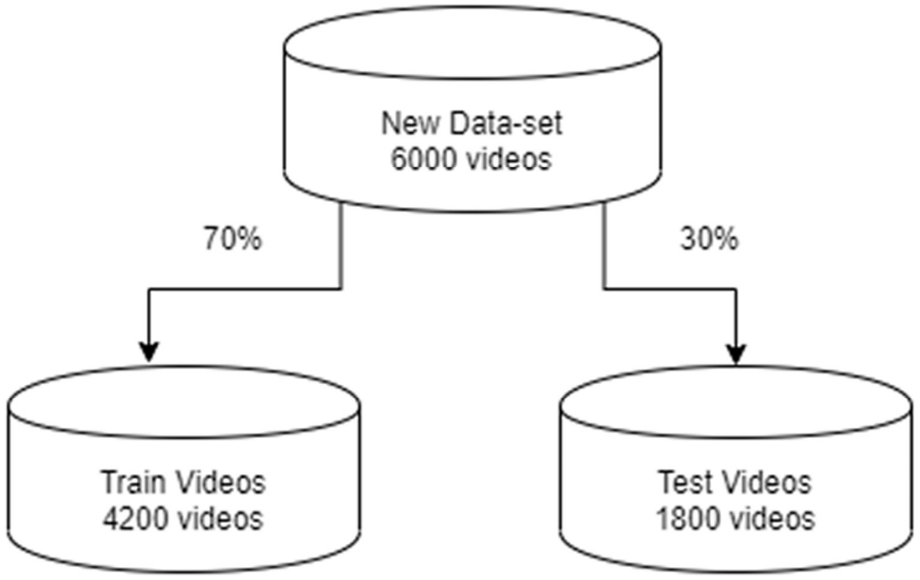
In this step, the videos are preprocessed and all the unrequired and noise is removed from videos. Only the required portion of the video i.e face is detected and cropped. The first steps in the preprocessing of the video is to split the video into frames. After splitting the video into frames, the face is detected in each of the frame and the frame is cropped along the face. Later the cropped frame is again converted to a new video by combining each frame of the video. The process is followed for each video which leads to creation of processed dataset containing face only videos. The frame that does not contain the face is ignored while preprocessing. To maintain the uniformity of number of frames, we have selected a threshold value based on the mean of total frames count of each video. Another reason for selecting a threshold value is limited computation power. As a video of 10 second at 30 frames per second(fps) will have total 300 frames and it is computationally very difficult to process the 300 frames at a single time in the experimental environment. So, based on our Graphic Processing Unit (GPU) computational power in experimental environment we have selected

150 frames as the threshold value. While saving the frames to the new dataset we have only saved the first 150 frames of the video to the new video. To demonstrate the proper use of Long Short-Term Memory (LSTM) we have considered the frames in the sequential manner i.e. first 150 frames and not randomly. The newly created video is saved at frame rate of 30 fps and resolution of 112 x 112.



Module 3: Data-set split

The dataset is split into train and test dataset with a ratio of 70% train videos (4,200) and 30% (1,800) test videos. The train and test split is a balanced split i.e 50% of the real and 50% of fake videos in each split.

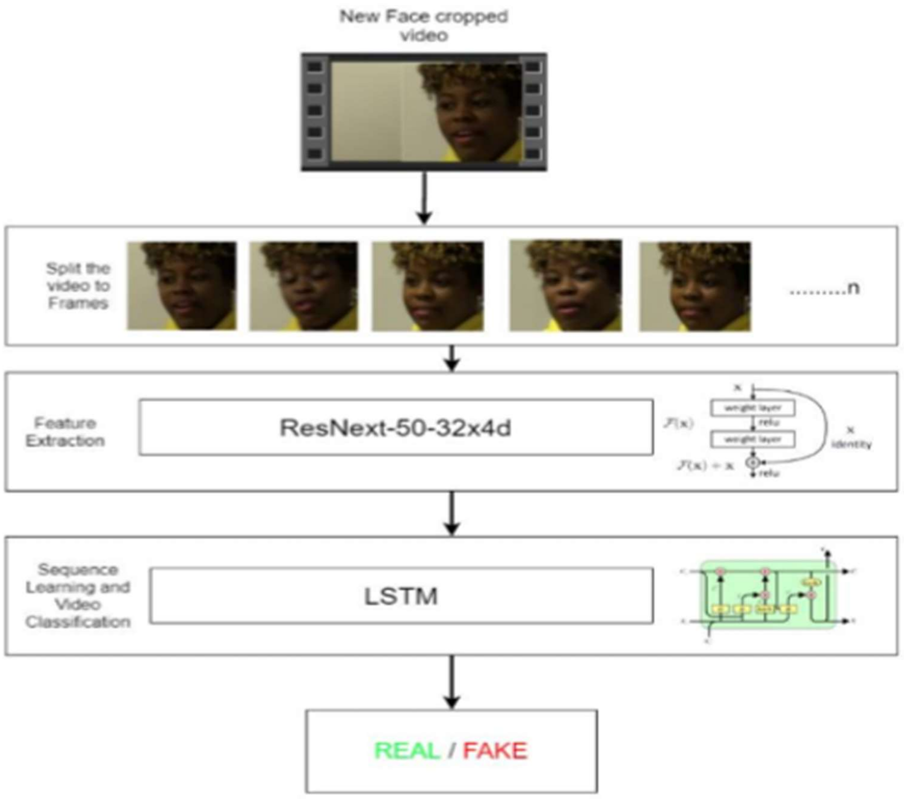


Module 4: Model Architecture

Our model is a combination of CNN and RNN. We have used the Pre- trained ResNext CNN model to extract the features at frame level and based on the extracted features a LSTM network is trained to classify the video as deepfake or pristine. Using the Data Loader on training split of videos the labels of the videos are loaded and fitted into the model for training.

ResNext : Instead of writing the code from scratch, we used the pre-trained model of ResNext for feature extraction. ResNext is Residual CNN network optimized for high performance on deeper neural networks. For the experimental purpose we have used resnext50_32x4d model. We have used a ResNext of 50 layers and 32 x 4 dimensions. Following, we will be fine-tuning the network by adding extra required layers and selecting a proper learning rate to properly converge the gradient descent of the model. The 2048-dimensional feature vectors after the last pooling layers of ResNext is used as the sequential LSTM input.

LSTM for Sequence Processing: 2048-dimensional feature vectors is fitted as the input to the LSTM. We are using 1 LSTM layer with 2048 latent dimensions and 2048 hidden layers along with 0.4 chance of dropout, which is capable to do achieve our objective. LSTM is used to process the frames in a sequential manner so that the temporal analysis of the video can be made, by comparing the frame at 't' second with the frame of 't-n' seconds. Where n can be any number of frames before t. The model also consists of Leaky Relu activation function. A linear layer of 2048 input features and 2 output features are used to make the model capable of learning the average rate of correlation between eh input and output. An adaptive average polling layer with the output parameter 1 is used in the model. Which gives the the target output size of the image of the form H x W. For sequential processing of the frames a Sequential Layer is used. The batch size of 4 is used to perform the batch training. A SoftMax layer is used to get the confidence of the model during predication.



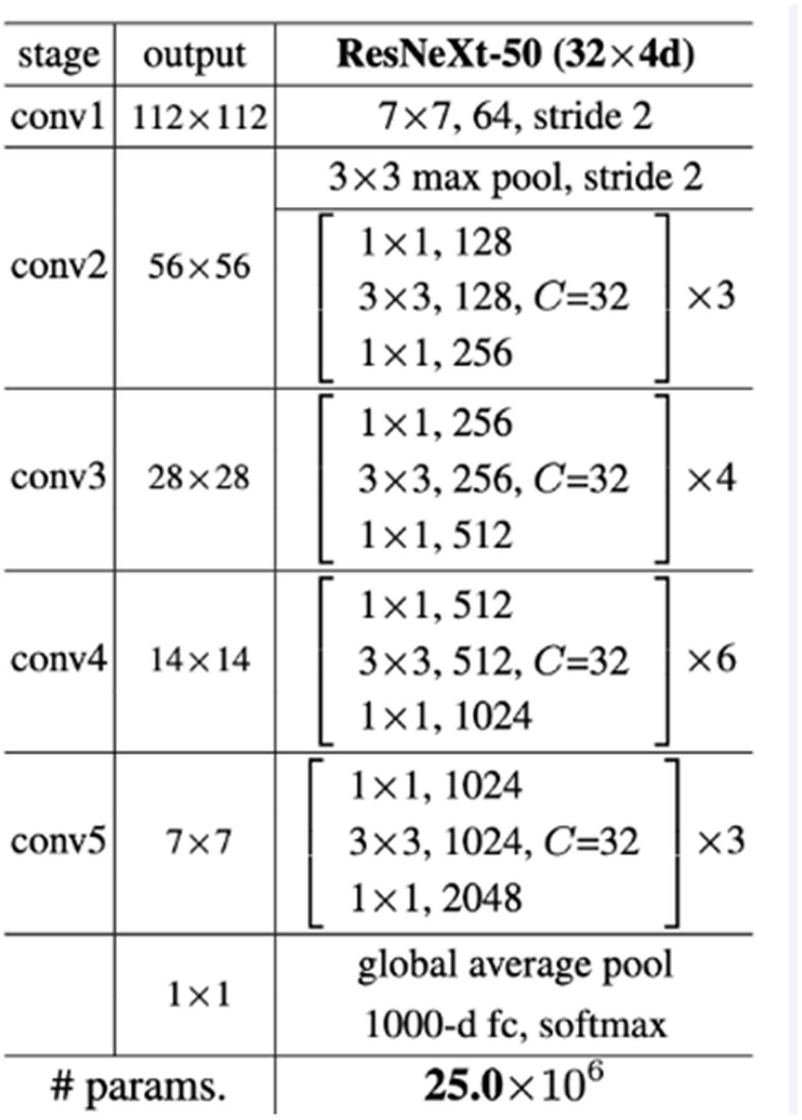
Module 5: Hyper-parameter tuning

It is the process of choosing the perfect hyper-parameters for achieving the maximum accuracy. After reiterating many times on the model. The best hyper-parameters for our dataset are chosen. To enable the adaptive learning rate Adam optimizer with the model parameters is used. The learning rate is tuned to 1e-5 (0.00001) to achieve a better global minimum of gradient descent. The weight decay used is 1e-3. As this is a classification problem so to calculate the loss cross entropy approach is used. To use the available computation power properly the batch training is used. The batch size is taken of 4. Batch size of 4 is tested to be ideal size for training in our development environment. The User Interface for the application is developed using Django framework. Django is used to enable the scalability of the application in the future. The first page of the User interface i.e index.html contains a tab to browse and upload the video. The uploaded video is then passed to the model and prediction is made by the model. The model returns the output whether the video is real or fake along with the confidence of the model. The output is rendered in the predict.html on the face of the playing video.

Model Details

The model consists of following layers:

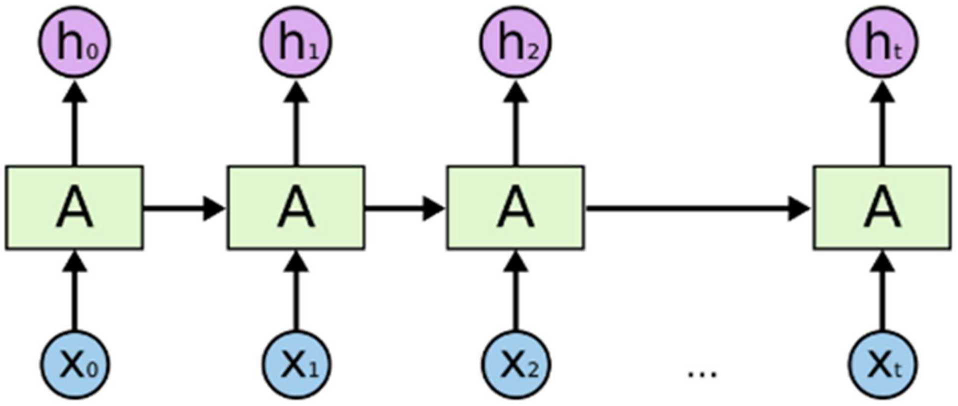
ResNext CNN: The pre-trained model of Residual Convolution Neural Network is used. The model name is resnext50_32x4d(). This model consists of 50 layers and 32 x 4 dimensions.

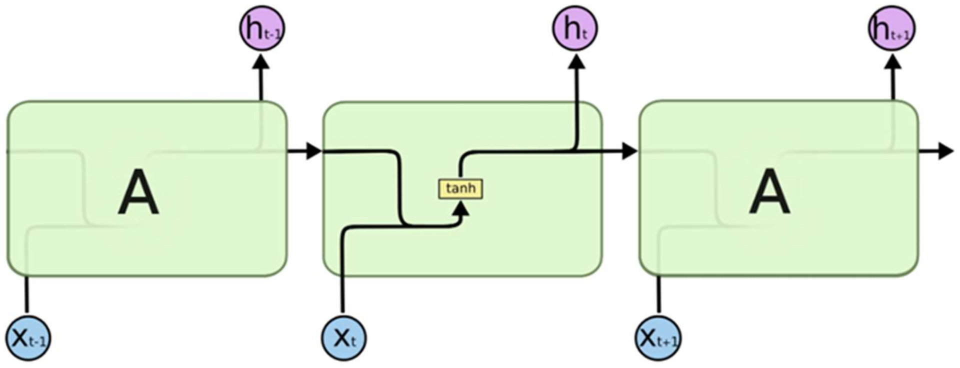


stage	output	**ResNeXt-50 (32×4d)**
conv1	112×112	7×7, 64, stride 2
conv2	56×56	3×3 max pool, stride 2
		$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128, C{=}32 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3	28×28	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256, C{=}32 \\ 1\times1, 512 \end{bmatrix}\times4$
conv4	14×14	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512, C{=}32 \\ 1\times1, 1024 \end{bmatrix}\times6$
conv5	7×7	$\begin{bmatrix} 1\times1, 1024 \\ 3\times3, 1024, C{=}32 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	global average pool 1000-d fc, softmax
# params.		$\mathbf{25.0}\times10^6$

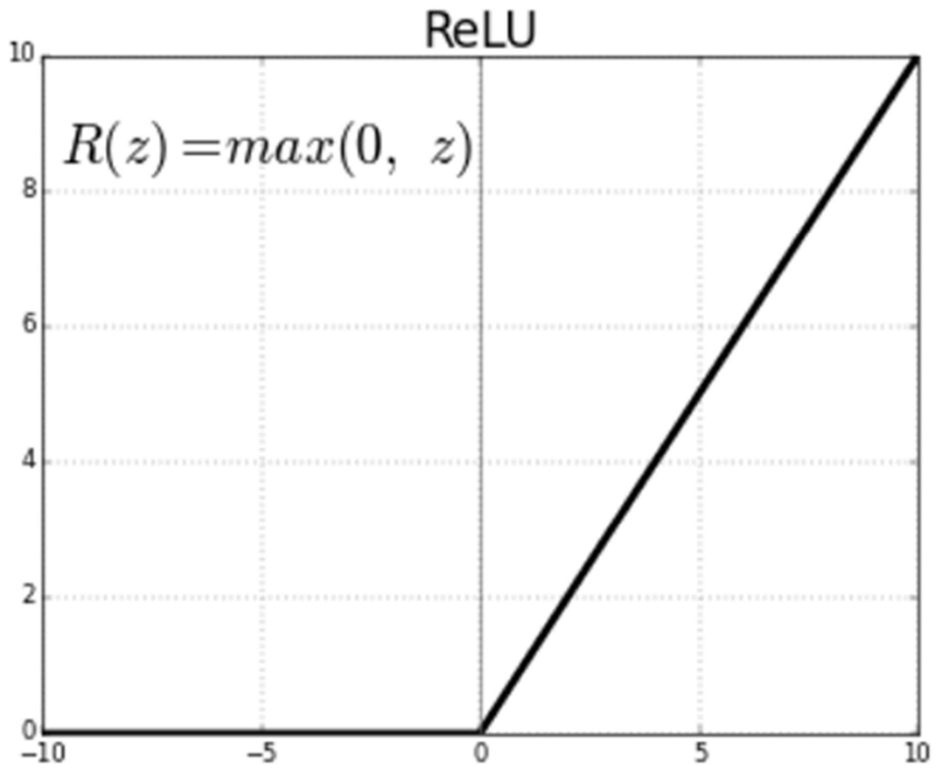
Sequential Layer: Sequential is a container of Modules that can be stacked together and run at the same time. Sequential layer is used to store feature vector returned by the ResNext model in a ordered way. So that it can be passed to the LSTM sequentially.

LSTM Layer: LSTM is used for sequence processing and spot the temporal change between the frames.2048-dimensional feature vectors is fitted as the input to the LSTM. We are using 1 LSTM layer with 2048 latent dimensions and 2048 hidden layers along with 0.4 chance of dropout, which is capable to do achieve our objective. LSTM is used to process the frames in a sequential manner so that the temporal analysis of the video can be made, by comparing the frame at ‘t’ second with the frame of ‘t-n’ seconds. Where n can be any number of frames before t.

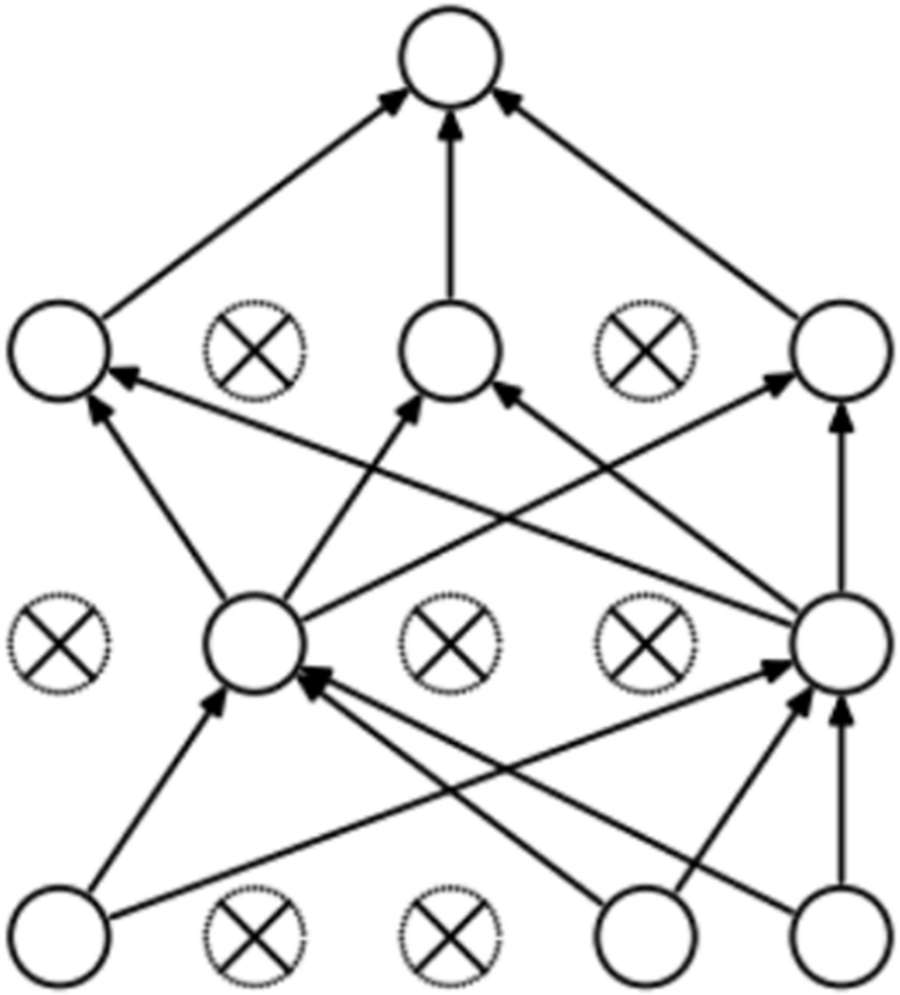




ReLU: A Rectified Linear Unit is activation function that has output 0 if the input is less than 0, and raw output otherwise. That is, if the input is greater than 0, the output is equal to the input. The operation of ReLU is closer to the way our biological neurons work. ReLU is non-linear and has the advantage of not having any backpropagation errors unlike the sigmoid function, also for larger Neural Networks, the speed of building models based off on ReLU is very fast.



Dropout Layer: Dropout layer with the value of 0.4 is used to avoid over fitting in the model and it can help a model generalize by randomly setting the output for a given neuron to 0. In setting the output to 0, the cost function becomes more sensitive to neighboring neurons changing the way the weights will be updated during the process of backpropagation.



Adaptive Average Pooling Layer: It is used To reduce variance, reduce computation complexity and extract low level features from neighbourhood.2 dimensional Adaptive Average Pooling Layer is used in the model.

Model Training Details

Train Test Split: The dataset is split into train and test dataset with a ratio of 70%train videos (4,200) and 30% (1,800) test videos. The train and test split is a balanced split i.e 50% of the real and 50% of fake videos in each split.

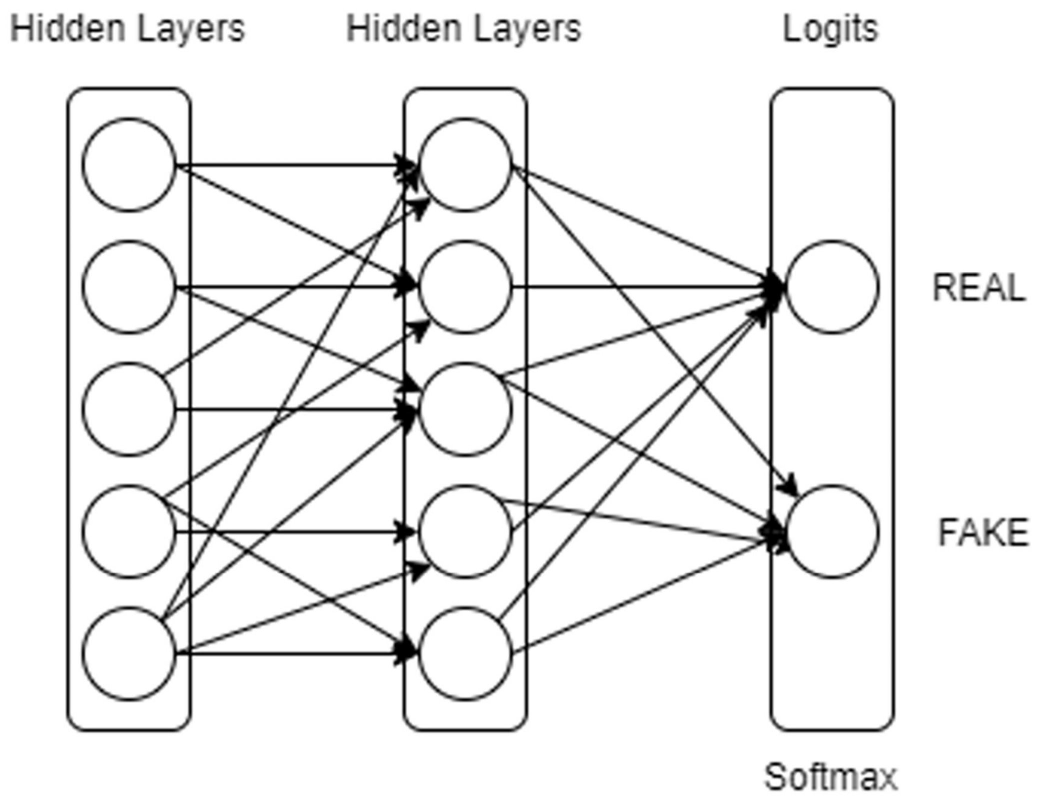
Data Loader: It is used to load the videos and their labels with a batch size of 4.

Training: The training is done for 20 epochs with a learning rate of 1e-5 (0.00001),weight decay of 1e-3 (0.001) using the Adam optimizer.

Adam optimizer: To enable the adaptive learning rate Adam optimizer with the model parameters is used.

Cross Entropy: To calculate the loss function Cross Entropy approach is used because we are training a classification problem.

Softmax Layer: A Softmax function is a type of squashing function. Squash ing functions limit the output of the function into the range 0 to 1. This allows the output to be interpreted directly as a probability. Similarly, softmax functions are multi-class sigmoids, meaning they are used in determining probability of multiple classes at once. Since the outputs of a softmax function can be interpreted as a probability (i.e.they must sum to 1), a softmax layer is typically the final layer used in neural network functions. It is important to note that a softmax layer must have the same number of nodes as the output later. In our case softmax layer has two output nodes i.e REAL or FAKE, also Soft max layer provide us the confidence(probability) of prediction.



Confusion Matrix: A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. The confusion matrix shows the ways in which your classification model is confused when it makes predictions. It gives us insight not only into the errors being made by a classifier but more importantly the types of errors that are being made. Confusion matrix is used to evaluate our model and calculate the accuracy.

Export Model: After the model is trained, we have exported the model. So that it can be used for prediction on real time data.

Conclusion

We presented a neural network-based approach to classify the video as deep fake or real, along with the confidence of proposed model. Our method is capable of predicting the output by processing 1 second of video (10 frames per second) with a good accuracy. We implemented the model by using pre-trained ResNext CNN model to extract the frame level features and LSTM for temporal sequence process ing to spot the changes between the t and t-1 frame. Our model can process the video in the frame sequence of 10,20,40,60,80,100.

Future Scope

There is always a scope for enhancements in any developed system, especially when the project build using latest trending technology and has a good scope in future. Web based platform can be upscaled to a browser plugin for ease of access to the user. Currently only Face Deep Fakes are being detected by the algorithm, but the algorithm can be enhanced in detecting full body deep fakes.