DETECTING FACIAL FORGERIES USING NOVEL FREQUENCY CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Facial expression recognition faces several challenges, including subjective nature, transient expressions, cultural differences, and cultural norms. To overcome these challenges, extensive datasets, techniques to capture nuanced emotions, and models that consider cultural and individual variances are needed. Advancements in computer vision and deep learning have made significant progress in facial expression identification, but more work is needed to improve accuracy, fairness, and practicality in real-world situations. Expression variability, ambiguity, occlusions, gender differences, data imbalance, overfitting, and lack of uniformity are common issues in the field. Ethical concerns, such as discrimination, privacy invasion, and monitoring, have led to discussions on the ethics of facial expression recognition. Cross-cultural variants, which occur across different cultures, impact how we recognize and express our emotions. Real-time processing is essential for systems that can detect and react to human emotions, but achieving low-latency recognition in real-world settings is challenging. Factors such as low-quality images, background noise, and dark lighting can make it more difficult to identify face emotions. Confidentiality issues arise due to facial expression recognition technology's use in public spaces and surveillance. Integrating findings to multi-modal data sets, which include written language, nonverbal gestures, and vocal signals, is a complex undertaking. Overall, overcoming these challenges requires a combination of computational and ethical considerations.

I. Introduction to Deep Learning in Facial Recognition

Deep learning has revolutionized face recognition, enabling the creation of algorithms that can identify more diverse faces than in the past. Facial recognition systems focus on face detection, which involves identifying and extracting faces from media such as photos and movies. CNN-based models like VGG Net, Res Net, and Inception have shown high levels of success in face identification by classifying a subject's face into identifiable identities. To address the challenge of identifying films with altered faces, researchers have researched the pros and cons of current facial video forgery detectors based on machine learning and deep learning. The suggested method is a frequency-based Conventional Neural Network (fCNN) architecture, which can learn certain frequency sub-bands from a video and identify a test video's legitimacy by using the unique frequency characteristics acquired during training.

To accomplish the goals mentioned earlier in the chapter, a frequency-based shallow CNN is designed and trained to authenticate videos. A publicly accessible bench marking dataset, Face Forensics++, is also used to evaluate the developed CNN-based detector. By designing and training a frequency-based shallow CNN to authenticate videos, researchers can improve the accuracy and efficiency of face verification systems and contribute to a more secure and trustworthy digital world.

Privacy and ethics-related concerns have become more prominent in the digital age, with concerns about data privacy, data breaches, mass surveillance, and illegal surveillance. Academics are interested in the subject of monitoring and surveillance, as government and business organizations engage in systematic monitoring of people's online activity and physical movements. Concerns regarding illegal surveillance have arisen in response to the persistent habit of tracking people's whereabouts via mobile devices and IoT sensors. Using AI-driven systems might lead to biased consequences by reinforcing inequalities and exacerbating preexisting societal biases. To address these concerns, new privacy safeguards, ethical standards, and regulations are required to protect individuals' rights and prohibit the misuse of facial recognition technology.

Facial recognition, a crucial aspect of modern technology, has made significant strides in recent years but still faces numerous challenges and limitations. One of the most significant challenges is the lack of transparency in data sharing processes, which can lead to a lack of informed consent for data sharing. Additionally, the absence of clarity in privacy policies can make it difficult to understand how data is used.

To ensure ethical advancements in AI and ML, ethical criteria must be prioritized, including fairness, openness, and harm prevention. Accountability is essential for holding people and businesses accountable for their actions, but it may be challenging to determine who is responsible for AI-generated decisions that lead to mistakes or negative outcomes. Trust is also crucial in shaping public views, as consistent data breaches, unethical data practices, and biased AI decision-making may erode trust in institutions like governments, businesses, and tech companies. Regulatory and legal frameworks, such as the EU's General Data Protection Regulation (GDPR) and California's Consumer Privacy Act (CCPA), are set up to protect individuals' rights to privacy. Governments have enacted data protection regulations to preserve individuals' rights to privacy, granting them more control over their personal information and subjecting them to strict duties for data processing.

Academics are interested in and should investigate further the question of permission when it pertains to data pertaining to minors, as the limited ability of children to provide informed consent and the potential risks connected with data collection and targeting are crucial. There are concerns about the privacy of ostensibly anonymous data, as anonymity methods may not be successful enough when faced with advanced data re-identification capabilities. Face recognition is a complex and multifaceted challenge that requires careful consideration and adaptation to various factors. By addressing these challenges, we can work towards making face recognition more efficient, fair, and ethical in the future.

II. Privacy and Ethics-Related Issues

The increasing use of facial recognition technologies has raised ethical and privacy concerns, as they can compromise people's privacy and lead to profiling, monitoring, and surveillance. Strict regulations, open data management practices, and strong privacy frameworks are needed to protect individuals' rights and mitigate these issues. Data privacy is a top priority in modern culture, with concerns about the collection, storage, and use of sensitive personal information. AI-enabled devices can gather location data, making it easier to monitor people without their knowledge or consent. Algorithmic bias, where AI algorithms learn prejudices from the data they use for training, can lead to biased or unjust outcomes, particularly in sectors like loan or employment. Underprivileged groups may be disproportionately affected by these discriminatory effects, exacerbated social biases, and perpetuating existing inequalities. Informed consent is essential in research ethics, but a lack of transparency is common with AI systems, making it difficult for customers to understand how their data is being used and for what purposes. Privacy-Preserving AI, which focuses on safeguarding people's personal information, is becoming more important in AI. Compliance management is a hot topic in various markets, with the General Data Protection Regulation (GDPR) and other privacy legislation being part of an ongoing effort to develop legal and regulatory frameworks for AI to implement ethical standards.

The process of minimizing prejudice

Methods like fairness-aware machine learning and bias audits may help reduce the prevalence of prejudice in artificial intelligence (AI) models and algorithms, which is essential for fostering ethical behaviour.

Effective governance and organizational performance are ensured by adhering to the principles of openness and accountability.

Developers and organizations working on AI must priorities transparency in all their endeavour and own up to the ethical and privacy concerns raised by their technology.

Developing AI in an ethical manner requires following rules and principles that highlight the importance of fairness, openness, and harm reduction.

To empower users to make educated choices about their personal data and interactions with AI systems, it is important to raise user awareness and provide education on data privacy and artificial intelligence (AI).

Facial forgery detection methods in publications such as [45], [38], [40], etc., used face features in the spatial domain to determine whether the image was altered or not. Researchers have created intricate designs such as GAEL Net [56] and Exception Net [44] to meticulously use the spatial domain artefact in the face-manipulated films. Nevertheless, more accurate findings may be achieved by analyzing the forgery detection issue in the frequency domain. The authors of [55] developed a classifier that uses spectra to identify fake photos. Experimental comparisons between frequency domain and spatial domain classifiers were carried out by the writers. I noticed that classifiers based on the spectrum performed better than the pixel-based classifiers.

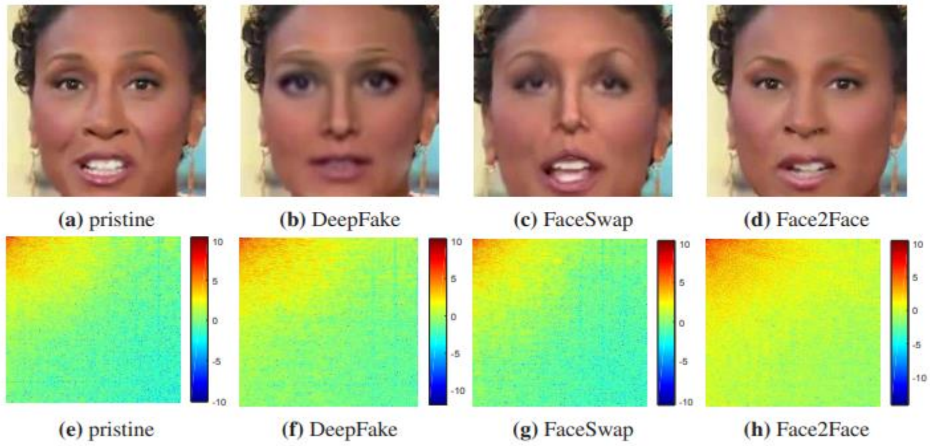


Figure 1: What you see here is a colour map representation extracted faces from 067.mp4 together with their accompanying 2D-GDCT coefficients.

The faces of pristine, Deep Fake, Face Swap, and Face2Face from the Face Forensics++ datasets are represented by (a) to (d) accordingly. For each face in (a)–(d), the 2D-GDCT coefficients are shown in color map form in (e)–(h).

Videos with altered faces, such as Deep Fakes, are created using GANs or auto encoders. Using high-dimensional GDCT face recovered from 067.mp4 pristine film and its matching facially altered movies, Deep Fakes, Face Swap, and Face2Face, auto encoders and GANs work by mapping the low-dimensional latent space. 2D GDCT is used to convert these retrieved faces into frequency domain. Additionally, they are shown visually as a color map. To comprehend the changes made to the various frequency bands during forging, the color map representation in the frequency domain face is used. The color map shows the low frequency sub-band in the top left corner and the high frequency sub-band in the bottom right corner. The zigzag pattern, which runs from the left to the right, represents the magnitude frequency sub-bands. For the 2D GDCT coefficient, a dark red colour indicates a high value and a dark blue colour a low value in the color map representation.

Discrete Cosine Transform (DCT) is the gold standard when it comes to frequency domain transformations. The energy compaction is one of DCT's main advantages, which is why it is often used in multimedia compression methods. The energy compaction feature causes the low frequency sub-spectrum of a picture to include the majority spatial domain's significant information.

The characteristics in the spatial domain are transformed into the frequency domain using the discrete cosine transform. By applying various frequencies to a series of N data points, it converts them into a sum of cosine functions. Sequence DE-correlation and energy compaction are the two fundamental features that the transform operates on.

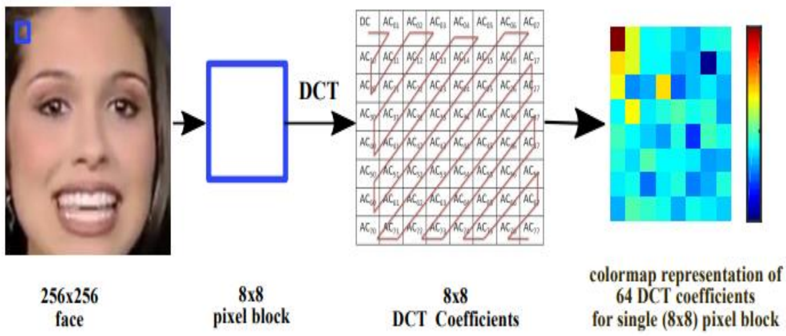


Figure 2: The frequency domain transformation (DCT) of input(face) and its color map representation.

The distinct cosine change, when applied on full face alternatively of blocks, is termed as Global

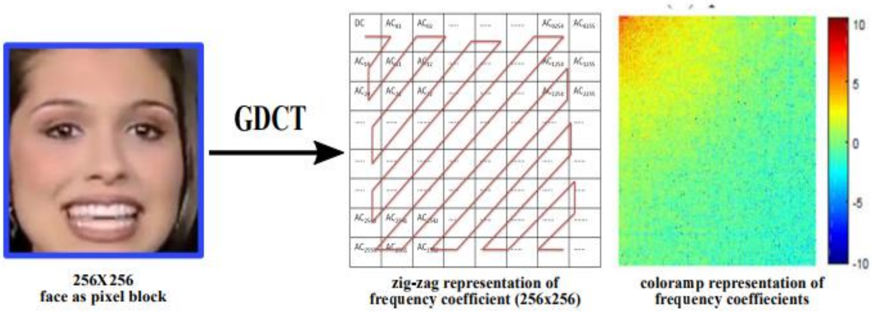


Figure 3: The frequency domain transformation (GDCT) of input(face) and its color map representation.

III. PROPOSED FREQUENCY CNN (fCNN)

A new approach to identifying films with and without modifications, such deepfakes or other types of media manipulation, is the frequency Convolutional Neural Network, or fCNN. Frequency domain analysis is the major focus of this technology. It involves converting video frames into frequency representations in order to reveal minor changes between the real and modified content. A 2D matrix is generated from the frequency representation of each video frame, which exposes features based on frequencies. Based on the identified anomalies, the fCNN classifies the video as real or false after processing the 2D matrix and extracting features from the frequency data. Using datasets that offer high-quality, diverse, and challenging examples of both real and edited videos is vital for training and evaluating a frequency Convolutional Neural Network (fCNN) for deepfake or changed video identification. Because fCNN uses frequency-domain analysis, the ideal datasets would include videos that have been subtly altered to change their frequency characteristics.

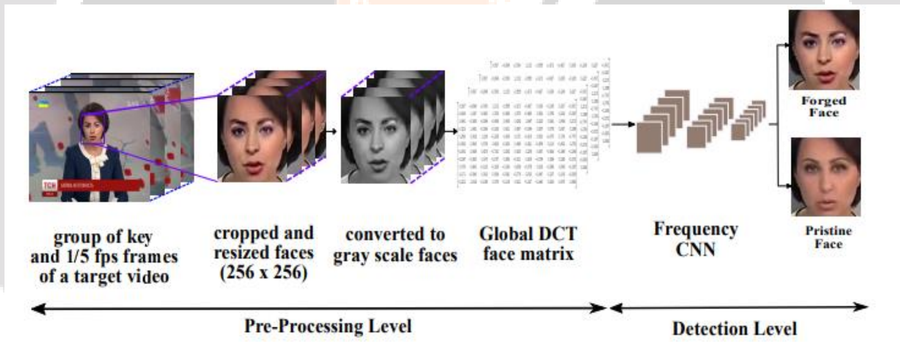


Figure 4: The block diagram of proposed frequency CNN.

Employed for extracting faces from greyscale video frames. Although proposed in 2001, the Viola Jones object identification framework excels beyond traditional CNN-based alternatives in the task of extracting frontal faces from images. The Viola-Jones algorithm consists of AdaBoost, a cascade classifier, and a feature extraction method akin to Haar. The initial step involves converting the input image into an integral image representation to differentiate between images containing faces and those that do not. Next, Haar features are extracted from this representation and passed on to AdaBoost and cascade classifiers. The Viola Jones method utilizes six Haar basis functions to extract features of facial traits such as the eyes, nose, mouth, and lips. To achieve efficient and rapid facial recognition, we employ AdaBoost and cascade classifiers.

Figure 5: An example to represent the output of Viola-Jones face detection algorithm.

scales slide across the granted frame and infusion Haar features. These extracted Haar characteristic are passed to Waterfall classifier for detection of face.

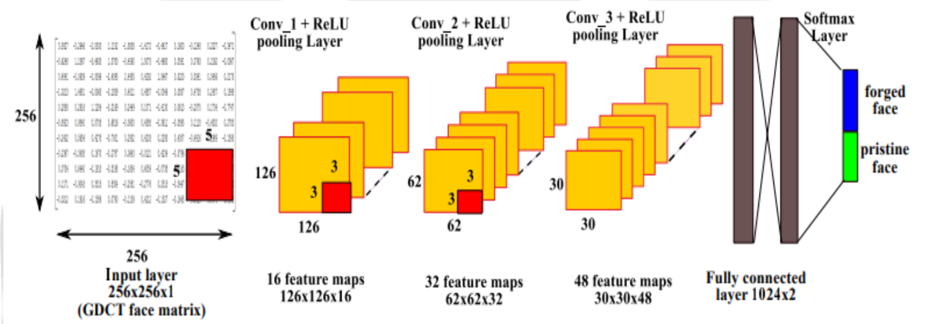
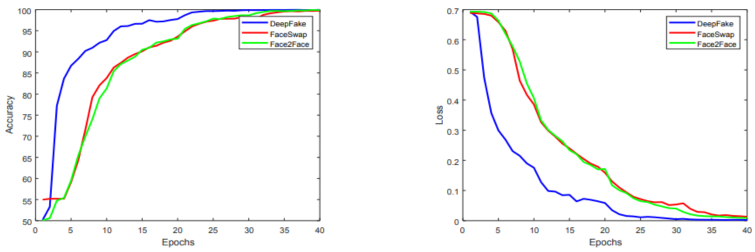


Figure 6: The architectural representation of proposed fCNN.

In order to identify the fake video, the detection level uses the target video's frequency converted face. Using conventional neural networks (CNNs), the major frequency-domain artefact of a fake video are recovered. The detection level makes use of CNNs because ir effectiveness in extracting intrinsic characteristics (described in chapter 2). This conventional neural network (CNN) is dubbed a frequency CNN (fCNN) since its primary purpose is to categories videos by extracting characteristics from the frequency domain. A three-layer conventional neural network, the suggested fCNN uses a pooling layer after each conventional layer and a ReLU activation layer [83] after each conventional layer. To mimic the proposed fCNN, this combination of three layers is repeated three times. In order to save computation, the pooling layer either summarizes the information supplied to the succeeding conventional layer or decreases the size feature maps. Flattening the features from the third pooling layer, dropout layer, and soft max layer is followed by the fully connected layer.

presented fCNN as a solution for both testing and training purposes. Starting with a random value for the kernel weights and biases is the first step in training. The suggested feed-forward network processes the 2DGDCT face sample. The sample is then sent to the soft max activation function for test class prediction after processing via conventional, ReLU, and pooling layers. The error is determined by comparing the projected and actual output. This estimated mistake is then sent back into the suggested neural network. By adjusting the weights, an misapplication process is used to reduce the calculated error. The suggested network makes use Stochastic Gradient Descent with Momentum (SGDM) optimization method, which has a learning rate of 0.001 and momentum of 0.9. To make the estimated production more accurate, all the weights are adjusted. Afterwards, the procedure is iterated till the error level is minimal. The weights are not changed further after the error approaches the lowest value, and the model is deemed trained.



(a) (b)

Figure 7: (a) and (b) represent the validation accuracy curve and loss curve respectively, of proposed fCNN c23 Face Forensics++ datasets, namely Deep Fake, Face Swap and Face2Face facial forgeries.

The datasets used to train and evaluate fCNN are discussed in depth in this section. Here we go into further detail about the performance measurements used to test how well the suggested detection approach holds up. The evaluation computational complexity suggested fCNN follows.

We thoroughly test the suggested fCNN approach using the Face Forensics++ [5] and Celeb-DF(v2) [6] datasets in various circumstances. One large and well-liked facial manipulation datasets is Face Forensics++ [7]. Video Graphic Array (VGA): 640 x 480, High Definition (HD): 1280 x 720, and Full High Definition (FHD): 1920 x 1080 are the precise resolutions videos included in the collection. Falsified movies based on expressions and identities are both included in this collection. Face2Face is based on facial expressions, while Deep Fakes and Face Swap are based on identities. There are three thousand films that make up each facial forgeries, with three hundred videos including altered faces and one thousand videos showing unaltered faces. There are three different compression grades applied to these videos: uncompressed (c0), light compressed (c23), and high compressed (c40). For each compression quality, the suggested approach is trained and tested. The 1000-video datasets is split into two parts: the training group has 850 movies, and the testing group contains 150 films. The 850-video training set is further subdivided into 700 training videos and 150 network validation videos. In order to get the frequency domain face samples needed for testing and training, the face extraction approach described in section 5.4.1 is used.

For binary detection of facial forgeries, shows the amount of face data used for training and testing fCNN.

	DeepFake		FaceSwap		Face2Face		Pristine	
Dataset	Training	Testing	Training	Testing	Training	Testing	Training	Testing
c0	5386	819	4430	693	5430	820	5380	827
c23	5362	817	4435	694	5461	822	5463	843
c40	5379	824	4424	687	5443	825	5348	814

Also tested against the Celeb-DF(v2) [6] datasets is the suggested fCNN's robustness. Based on their studies, the authors of [36] found that out of all the datasets available in the literature, the Celeb-DF(v2) datasets had the lowest average Area Under the Receiver's Curve (AUC). Because of this, detecting Celeb-DF(v2) is difficult. There are 59 films of famous people from several age groups, geographies, and ethical spectrum in the Celeb-DF(v2) [6] datasets. The datasets is inclusive of films from both the male and female communities, ensuring that it is not biased towards either gender. We train and test our proposed fCNN on this datasets. With 5639 training movies and 516 testing videos, the datasets that is currently accessible contains Deep Fake. The suggested fCNN is trained and validated using these training videos.

The calculation of trainable parameters of proposed fCNN.

Layer (type)	Kernel size	Output Shape	Calculation	Trainable Parameters
Input Layer		256 x 256 x 1		0
conv2d_1 (Conv2D)	5x5	252 x 252 x 16	((5x5x1)+1)16	416
activation_1 (Activation)		252 x 252 x 16		0
max_pooling_2d_1	2x2	126 x 126 x 16		0
conv2d_2 (Conv2D)	3x3	124 x 124 x32	((3x3x16)+1)32	4640
activation_2 (Activation)		124 x 124 x32		0
max_pooling_2d_2	2x2	62 x 62 x 32		0
conv2d_3 (Conv2D)	3x3	60 x 60 x 48	((3x3x32)+1)48	13872
activation_3 (Activation)		60 x 60 x 48		0
max_pooling_2d_3	2x2	30 x 30 x 48		0
flatten_1		43200		0
dense_1		1024	(43200+1)1024	4423782
dropout_1		1024		0
dense_2		2	(1024+1)2	2050
Total trainable parameters				**44,258,802**

The total number of trainable parameters in a conventional neural network (CNN) includes both the parameters conventional layer and the fully connected layer. The output shape and trainable parameter calculations for each layer proposed fCNN are detailed here. Additionally, it reveals that the proposed fCNN has about 44 million trainable parameters.

The validation and testing accuracy (%) for different number of filters of 3 layered frequency CNN

No.of filters	Validation *Ac*	Testing *Ac*	Trainable Parameters
8,16,24	92.69	85.06	22126330
16,32,48	**93.99**	85.24	44258802
32,48,96	93.44	**86.08**	88532946

The validation and testing accuracy (%) for average and maximum pooling technique.

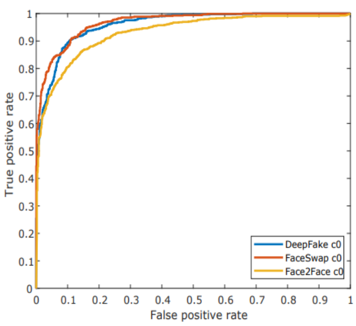
Pooling Technique	Validation *Ac*	Testing *Ac*
avg pool	87.88	84.76
max pool	**93.99**	**85.24**

The validation and testing accuracy for different dropout Pe.

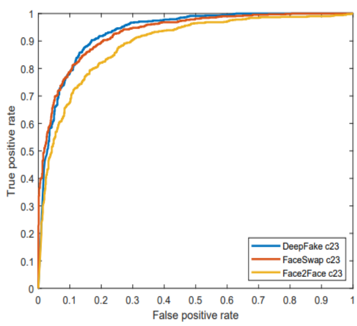
Dropout *Pe*	Validation *Ac*	Testing *Ac*
0.2	93.88	85.02
0.3	92.69	85.03
0.4	91.77	84.64
0.5	**93.99**	**85.24**

The validation and testing accuracy (%) for different batch sizes.

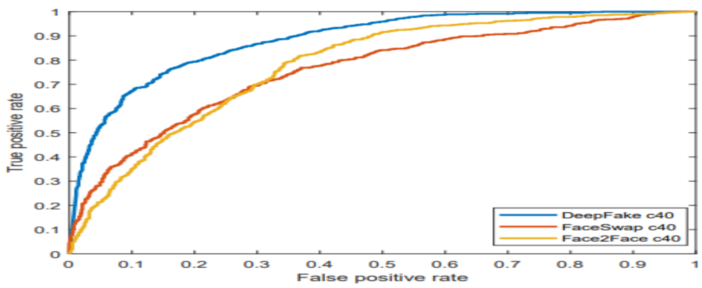
Batch Size	Validation *Ac*	Testing *Ac*
28	92.88	85.54
32	**93.99**	**85.24**



(a)



(b)



(c)

Figure 8: The Receiver Operating Characteristics (ROC) of facial forgeries on the Face Forensics++ dataset's compression characteristics at c0, c23, and c40.

However, the model still has room for development. One, hyper parameter tweaking, further training time, and polishing are always possible. However, retraining the feature extraction network—just the LSTM portion network was trained—is thought to have the most beneficial impact. This is probably why one benchmark models that uses the Exception network outperforms the ones suggested here. After being retrained for 15 epochs, this network was first loaded with the Image Net weights. Since object classification in movies is the intended use Image Net collection, it's not hard to see how this might have a significant impact. This means the network will pay more attention to traits that allow it to recognize faces than to pixel-level data that aid in determining whether the video is unaltered or altered. Unfortunately, the training was not viable for this project due to the excessive amount of time it would have required.

It should be mentioned that all the movies used for training and assessment were significantly compressed, much more so than those found on YouTube and social media. While all assessed architectures achieved near-perfect accuracy when utilizing raw, uncompressed movies, it is clear from the benchmarks that these lower-quality videos are far more challenging to categorize accurately [11]. Consequently, training the suggested architecture on less compressed data with more realistic compression coefficients is expected to provide better results. Importantly, we can't make any judgments about the network's performance without first testing how it would do without the retraining on these films.

Videos made using neural textures were the most difficult to identify, in contrast to deep fakes, which were obviously the simplest. The benchmark is no exception [11]. An investigation into the reasons behind this might provide more fruitful results; nonetheless, it is probable that the high quality movies included in the collection and the relative difficulty of different detection algorithms contribute to this phenomenon. Because the other movies altered the whole face, the one with the neural texture may have been easier to spot because it just altered the mouth area. There may be fewer artefact for the classifier to detect if the changed area is smaller.

Training a single network for each manipulation technique yielded better results than training all methods at once. It is not surprising that learning to recognize one kind of manipulation technique is simpler than simultaneously keeping track of four. When training on all manipulation techniques, the accuracy tended to rise with neural textures. We don't know why this is happening, but one possible explanation is that the network isn't able to recognize neural textures as signifier due to the tiny changed region, even if they produce artefact that are comparable to those of other methods. After learning to detect similar artefact in the training dataset's easier films, the network will do the same in neural texture videos.

Over the course of its five iterations of training and evaluation, the network maintained a relatively steady accuracy, but its true-positive-to-true-negative ratio fluctuated widely. Any feature extraction network would exhibit the same behaviour.

Every model's best performance on the DFDC test datasets is expected given that the model is trained on the DFDC train datasets. In contrast to Efficient Net, which achieves an AUC more than.952, Exception and ResNet-50 do poorly with AUCs of.695 and.642, respectively. For some reason, it does not seem that larger models provide better results from the Efficient Net networks (Tan and Le 2019). Among the four, EfficientNet-B4 has the highest area under the curve (AUC) at.974, while EfficientNet-B2 has the lowest at.952. With the exception comparison between EfficientNet-B0 and EfficientNet-B1, all findings are significantly different according to the Mann-Whitney U-Test.

Additionally, experiments using Face Forensics++, Celeb-DF, and Wild Deepfake were conducted to evaluate the models' ability to generalist to non-i.i.d. data. Surprisingly, none models fare very well on Face Forensics++; the best result was achieved by EfficientNet-B1, which had an area under the curve (AUC) of.559—just slightly higher than a random guess. According to the results on the DFDC, EfficientNet-B2 ranks second with an AUC of.802, while EfficientNet-B4 ranks first with an AUC of.805 on Celeb-DF. Curiously, EfficientNet-B3 deviates from this norm, exhibiting the lowest performance among the Efficient Nets with an AUC of.683. It makes no difference whether ResNet-50 or Exception is used for detection. The results on Wild Deep fake paint a similar picture. With an AUC of.797, EfficientNet-B4 outperforms EfficientNet-B3, which has a lower AUC of.647.

In the preceding section, we proved that the proposed fCNN achieves a high level of accuracy in identifying facial forgeries by discussing its binary classification on the Face Forensics++ and Celeb-DF(v2) datasets. To understand how fCNN activation maps contribute to the necessary accuracy, this paragraph explains the rationale behind it. Visualizing the information retrieved by the conventional layer kernels, activation maps provide an overview of a conventional neural network (CNN). The last classification layer, the soft max layer, uses these characteristics to make label predictions for the input data fed into CNN. Studying and analyzing these activation maps helps to understand how the proposed fCNN works and how accurate it is in identifying face forgeries. The suggested fCNN's activation map is retrieved by means procedure outlined in [4]. From the test datasets, fifty faces are chosen at random. The suggested fCNN is fed these fifty faces from each classes. The third conventional layer's feature maps are retrieved rather than the classification layer's output. The suggested fCNN stops short of doing any more feature extraction as it is the final conventional layer. This means that these features are the last ones that classify data. For every test face sample, a matrix with dimensions 60×60×48 is produced. The next step is to calculate the mean of four characteristics that are chosen at random. Color maps are used to assess these four average activation maps.

The effect of frame rate on identification of identity swapped videos is one related topics. When tested on the Celeb-Df test datasets, the proposed model outperformed the other frame selection techniques by at least 2.1% and baseline model 1 by 1.8%, according to the AUC values shown in Figure 6 and Table 3. Since this approach uses 10 frames instead of 5 frames, it should come as no surprise that it outperforms the 30-frame interval. In addition, frame selection approaches that rely on the first ten or twenty frames are able to record details on the changeover between successive frames. In contrast, systems that use an equal interval to choose frames are able to capture larger disparities between them. Consequently, models that use an equal interval method are better able to discern larger disparities among the chosen frames within a lengthier video sequence. A frame selection technique based on the first 10 or 20 frames in both models performs worse than an equal interval strategy, which may lose dynamic information between subsequent frames. However, this strategy still beats the other option. Moreover, despite training on 5 extra frames, the initial 10 frame selection technique is 3.1% less accurate than the equivalent interval of 30 frames approach. This proves that fewer frames are required for accurate Deep fake video detection using an equal interval method.

From 77.1% accuracy on the training datasets to 71.0% accuracy on the validation datasets, the performance proposed model trained on the first 20 frames reduces by 6.1%. This suggests that the model is prone to over fitting more easily. When the model is trained on 5 frames with an identical interval of 30, the difference between the training and validation accuracy is decreased to 0.3%. This model was less susceptible to over fitting than the frame selection approaches that relied on consecutive frames, even if it did not get the best results. A possible reason is that models with an excessive amount of training data tend to acquire intricate patterns within the data, making it difficult for them to generalize to new data.

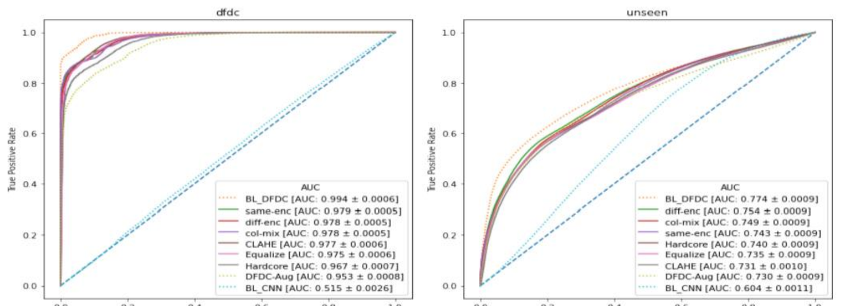


Figure 9: The ROC-AUC curve baselines, augmentation tests, and ensembles on the DFDC test datasets and on the results of all unseen datasets.

In order to verify a video that has been altered to include a person's face, this chapter adds to an innovative network called a frequency-based shallow Conventional Neural Network (fCNN). When using CNN for video classification, researchers often use characteristics from the spatial domain. Nevertheless, when it comes to detecting fake videos, the frequency domain characteristics work just as well. Blurring is a telltale sign of auto encoder-based facially altered videos. Investigating these fingerprints in the frequency domain also improves them. These findings inspired the development and implementation of a frequency-based CNN for the purpose of forgery detection by means extraction of unique frequency sub-band properties. The faces collected from a video are transformed into frequency domain using the Global Discrete Cosine Transform (GDCT). The three conventional layers fCNN architecture are fed these frequency domain faces.

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