Decoding Deepfake Detection: Harnessing the Strengths of Traditional Machine Learning for Superior Accuracy

P.Yogendra Prasad[1] , Maddula Lohitha[2] , Gandikota Sairam Roopak[3*], Dommaraju Sai Harshini[4], Kandipati Sumanth[5]

[1]Assistant Professor, Dept. of CSSE, Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College), Tirupati.India
[2,3,4,5]UG Scholar, Department of Computer Science and Systems Engineering, Sree Vidyanikethan Engineering College, Tirupati, India.

[1]yogendraprasad.p@vidyanikethan.edu
[2]lohitha.m003@gmail.com
[3]roopakgandikota12@gmail.com
[4]harshinisai726@gmail.com
[5]sumanthkandipati@gmail.com

Abstract. This comprehensive study delves into the dynamic landscape of deep learning applications, focusing on the burgeoning realm of deep fakes. Deep learning has seamlessly integrated into fields like natural language processing, machine learning, and computer vision, giving rise to innovative applications. However, the surge in deep fakes, sophisticatedly manipulated videos/images, has become a pressing concern. The nefarious applications of this technology, such as fake news, celebrity impersonations, financial scams, and revenge porn, pose significant threats in the digital realm. Particularly, public figures like celebrities and politicians are highly susceptible to the Deep fake detection challenge. This research systematically assesses both the production and detection aspects of deep fakes, employing diverse deep learning algorithms, including InceptionResnetV2, VGG19, CNN, and Xception. The evaluation, conducted on a Kaggle deep fake dataset, highlights Xception as the most accurate among the algorithms studied. As malicious uses of deep fakes escalate, the imperative for robust detection mechanisms intensifies to safeguard against potential societal consequences.

Keywords: Deep Learning, Fake Detection, InceptionResnetV2, VGG19, CNN, and Xception.

1 Introduction

Deepfake technology, driven by advanced machine learning techniques, has emerged as a powerful tool for creating highly convincing fake videos and images by seamlessly

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_39

superimposing one person's likeness onto another. This has highlighted substantial worries regarding the possible abuse of synthetic media technology for malicious purposes, such as spreading misinformation or manipulating public perception. In response to this growing threat, researchers and technologists have turned to deep learning approaches to develop effective deepfake detection methods. Advanced machine learning, especially the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has shown promise in identifying subtle inconsistencies and artifacts present in deepfake content. Several studies have contributed to the advancement in identifying synthetic media fabrications techniques. Notably, research by H. Li et al. introduced a deep learning-based method utilizing facial action units to identify manipulated facial expressions in videos (Li et al., 2020). Additionally, work by A. Rossler et al. proposed using deep learning to analyze subtle head movements and blinking patterns to uncover anomalies indicative of deepfake content (Rossler et al., 2019). This introduction explores the burgeoning field of deepfake detection through deep learning, highlighting the urgency and significance of addressing the challenges posed by this rapidly evolving technology. The subsequent sections delve into specific methodologies, advancements, and challenges associated with deepfake detection, shedding light on the continuous endeavors to protect the authenticity of online content an era dominated by sophisticated AI-generated manipulations. This study explores deep learning applications in addressing the growing concern of deep fakes, manipulated videos/images. Investigating diverse algorithms like InceptionResnetV2, VGG19, CNN, and Xception on a Kaggle deep fake dataset, the research emphasizes the need for robust detection mechanisms amid rising malicious uses in fake news, scams, and privacy breaches. Proliferation of deep fakes, convincingly altered videos/images, poses a grave threat in various domains, including misinformation dissemination and privacy breaches. This study addresses the pressing need to comprehend and counteract the malicious applications of deep fakes, emphasizing the urgency in developing effective detection methodologies.

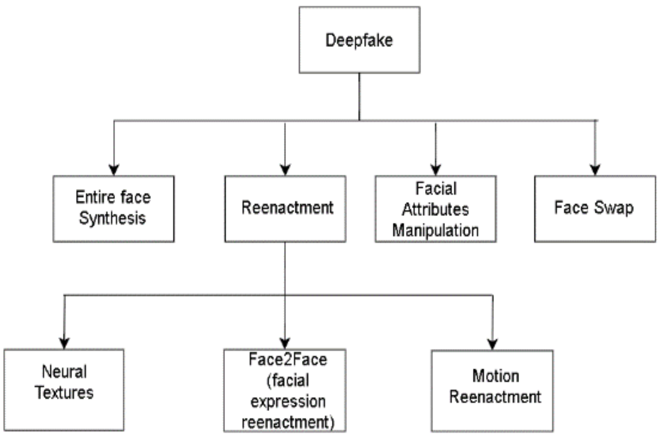

Fig1: A Comprehensive overview of Deepfake.

2 Related Work

The existing system focuses on the analysis and utilization of previously deployed deep fake detection algorithms. It extensively explores classic detection methods and contemporary deep learning-based approaches, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM). Classic methods often rely on rule-based heuristics, while deep learning methods harness the hierarchical learning capabilities of neural networks to discern intricate patterns indicative of deep fakes. The research seeks to offer a thorough insight into the advantages and limitations of these methods in identifying manipulated content. In contrast, the proposed system takes a proactive stance by integrating cutting-edge deep learning algorithms. The proposed system aims to enhance detection accuracy, contributing to a deeper comprehension of deep fake production and distribution for more effective countermeasures. The existing system relies on traditional and contemporary methods, potentially limiting adaptability to emerging deep fake techniques. Classic methods reliance on rule-based heuristics may struggle with the evolving sophistication of deep fake creation, leading to decreased accuracy. While deep learning methods are employed, the existing system may lack a comprehensive understanding of the intricate patterns characterizing evolving deep fake technologies. Depending on data complexities, the existing system may exhibit variable accuracy, potentially rendering it less reliable across diverse scenarios. Several studies have explored diverse methodologies for detecting deepfake videos, taking into account various factors. One notable aspect considered by Chawla et al. [6] is the blinking rate of humans, which typically occurs every two to ten seconds, with each blink lasting about half or a quarter of a second. Notably, individuals in deepfake videos tend to exhibit reduced blinking, contributing to a slight distinguishability from authentic videos. Due to the diverse array of techniques employed in the creation of deepfakes, constructing a network capable of discerning distinguishing features becomes challenging without a dataset encompassing these varied methods. Acknowledging the distinct characteristics inherent in deepfake generation, we address this challenge by training our model on a dataset containing deepfake videos generated through a spectrum of techniques. In contrast to the manual detection carried out by human observers, Convolutional Neural Networks (CNNs) prove effective in identifying deepfake content through the analysis of image features [14]. Neural networks empower computers to learn from attributes that could be challenging for the human vision to discern. In the work of Do et al., a CNN was implemented, employing a fine-tuning method that yielded an accuracy surpassing 70% across three distinct image datasets. This illustrates the capability of CNNs to excel in automated detection tasks related to deepfake content through the extraction and analysis of intricate image features.

3 Proposed Methodology

i) Proposed Work: The proposed system aims to combat the escalating threat of deep fakes through an integrated approach leveraging cutting-edge deep learning algorithms. Utilizing a Kaggle deep fake dataset, our system employs InceptionResnetV2, VGG19, CNN, and Xception algorithms for comprehensive evaluation. The emphasis is on developing a robust detection mechanism to discern authentic content from manipulated ones. By scrutinizing the intricacies of deep fakes, the system aspires to contribute to a deeper understanding of their production and distribution. The integration of multiple algorithms ensures a nuanced analysis, while the dataset provides a diverse range of scenarios for effective training and testing. This holistic approach aims to improve the overall accuracy and reliability of deep fake detection, mitigating the potential societal consequences of fake news, impersonations, and privacy violations. The proposed system stands as a pivotal step toward fortifying our digital landscape against the malevolent misuse of deep fake technology.

ii) System Architecture:
The system architecture for deepfake detection involves a multi-step process encompassing the importation of deepfake videos, slicing them into frames, exploratory data analysis (EDA) with data visualization, image resizing, and leveraging an image data generator. Following EDA, the system applies various deep learning algorithms, including InceptionResNetV2, VGG19, CNN, and Xception, for robust detection. Initially, deepfake videos are imported into the system, where they undergo a segmentation process, slicing them into individual frames. This frame-level approach enables a more granular analysis of potential manipulations within the video content. The subsequent EDA phase involves data visualization techniques to gain insights into the characteristics of the frames, contributing to a comprehensive understanding of the dataset. To enhance model generalization, image resizing is employed to standardize frame dimensions. Additionally, an image data generator is utilized to augment the dataset, introducing variations and improving model robustness. The core of the architecture lies in applying deep learning algorithms such as InceptionResNetV2, VGG19, CNN, and Xception, known for their effectiveness in image classification tasks. Each algorithm processes the frames independently, extracting distinctive features that contribute to the overall detection accuracy. The final stage involves a comparison of the detection efficiency of these computational methods, evaluating metrics such as accuracy, precision, recall, F1-score, specificity, sensitivity, MAE and MSE. This comprehensive system architecture ensures a systematic and efficient approach to deepfake detection, leveraging a combination of preprocessing, exploratory analysis, and cutting-edge deep learning computational methods to enhance the system's overall efficacy.

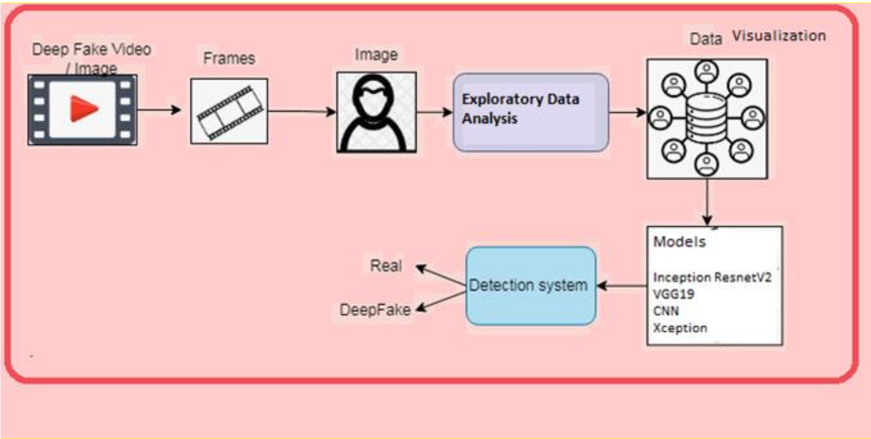

Fig 2: System Architecture

iii) Dataset collection:

For the purpose of deepfake detection model development, a Kaggle deepfake dataset serves as a valuable resource, providing a diverse and extensive collection of manipulated and authentic video content. Kaggle, a platform for data science and machine learning competitions, offers curated datasets that are particularly relevant for addressing the challenges posed by deepfake technology. The dataset collection process begins with accessing Kaggle's repository of deepfake datasets, which typically includes a substantial number of videos showcasing both genuine and manipulated content. These videos are meticulously annotated to designate their authenticity, forming a labeled dataset conducive to supervised learning approaches. The dataset encompasses a variety of actors, scenes, and contexts to ensure the model's robustness and generalization across diverse scenarios. Given Kaggle's collaborative nature, contributors often share their expertise in preparing and augmenting datasets, enhancing their quality and usability for research purposes.

iv) Image Processing:

Image processing is a crucial aspect of developing effective computer vision models, particularly in applications like deepfake detection. Two fundamental image processing techniques employed in this context are Image Resizing and Image Data Generator. Image Resizing involves adjusting the dimensions of images to a standardized format, ensuring uniformity in input data for deep learning models. Resizing is essential for handling images of varying resolutions, preventing computational inefficiencies, and facilitating seamless integration into neural network architectures. It helps strike a balance between computational efficiency and preserving critical visual information. On the other hand, Image Data Generator is a technique that enhances dataset diversity and augments model robustness by introducing variations in the input data. This includes random transformations such as rotation, zooming, and horizontal flipping. For deepfake detection, Image Data Generator plays a pivotal role in training models capable of handling real-world variations and manipulations within video frames. Together, these image processing techniques contribute to the preparatory stages of developing a reliable deepfake detection system. Image Resizing ensures consistency in input dimensions, while Image Data Generator enhances the model's ability to generalize by introducing variability, ultimately improving the model's capacity to discern authentic content from manipulated visual data. These techniques collectively empower the deep learning model to navigate the complexities of diverse and dynamic visual inputs encountered in real-world scenarios.

v) Data Visualization:

Slicing videos into frames is a pivotal step in deepfake detection, enabling a granular analysis of temporal manipulations within video content. Once videos are segmented into individual frames, data visualization techniques become instrumental in gaining insights into the characteristics of the dataset. Data visualization in this context involves the representation of visual information extracted from video frames through various graphical and statistical means. Techniques such as plotting histograms of pixel intensities, frame duration distributions, and visualizing optical flow patterns provide a comprehensive understanding of the dataset's temporal dynamics. Histograms can reveal variations in pixel values, aiding in identifying anomalies or patterns associated with deepfake manipulations. Temporal visualizations, such as frame-by-frame comparisons or motion heatmaps, contribute to discerning irregularities or artifacts introduced by deepfake generation processes. Plotting optical flow vectors helps visualize the direction and intensity of motion between consecutive frames, offering insights into dynamic aspects of the video content. Moreover, the use of interactive visualization tools allows researchers to explore and annotate specific frames, facilitating the identification of patterns or anomalies that may be indicative of deepfake manipulations. By employing these data visualization techniques, researchers can unravel intricate temporal patterns, anomalies, and artifacts within the dataset, providing valuable insights for refining deepfake detection models. Visualization aids in making informed decisions during the model development process and contributes to the overall interpretability of the deepfake detection system.

vi) Algorithms:

InceptionResNetV2: InceptionResNetV2, a fusion of Inception and ResNet architectures, is employed for its deep structure and superior feature extraction capabilities.

This model excels at capturing complex structures and layered characteristics, making it perfectly suited for detecting nuanced visual cues indicative of deepfake manipulations within video frames.

VGG19: VGG19, chosen for its simplicity and effectiveness, features a straightforward architecture with small receptive fields, aiding in capturing both low and high-level features. Its suitability for discerning patterns relevant to deepfake detection within individual video frames makes it a valuable choice.

CNN: A Convolutional Neural Network (CNN) is utilized for its efficiency in extracting spatial features from image data. This lightweight yet effective architecture is well-suited for efficiently processing individual frames during deepfake detection.

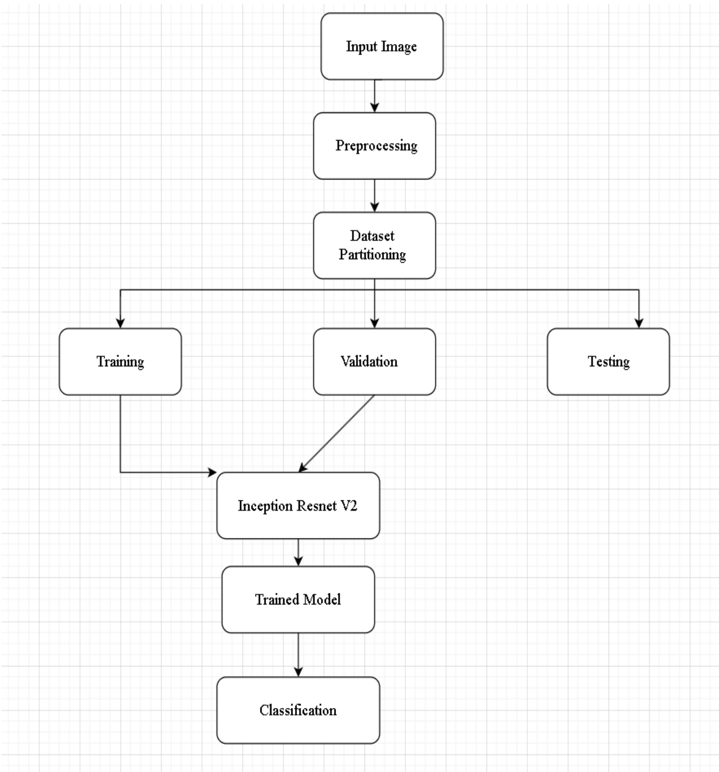

Fig-3: Model flow Diagram

Xception: Xception, with its deep architecture and exceptional feature extraction capabilities, is selected for its ability to understand spatial hierarchies. This model's depth enhances its capacity to capture intricate patterns relevant to detecting manipulations within video frames, making it a suitable choice for this project.The proposed system aims to combat the escalating threat of deep fakes through an integrated approach leveraging cutting-edge deep learning algorithms. Utilizing a Kaggle deep fake dataset, our system employs InceptionResnetV2, VGG19, CNN, and Xception algorithms for comprehensive evaluation. The emphasis is on developing a robust detection mechanism to discern authentic content from manipulated ones. By scrutinizing the intricacies of deep fakes, the system aspires to contribute to a deeper understanding of their production and distribution. The integration of multiple algorithms ensures a nuanced analysis, while the dataset provides a diverse range of scenarios for effective training and testing. This holistic approach seeks to enhance the overall accuracy and reliability of deep fake detection, mitigating the potential societal consequences of fake news, impersonations, and privacy violations.

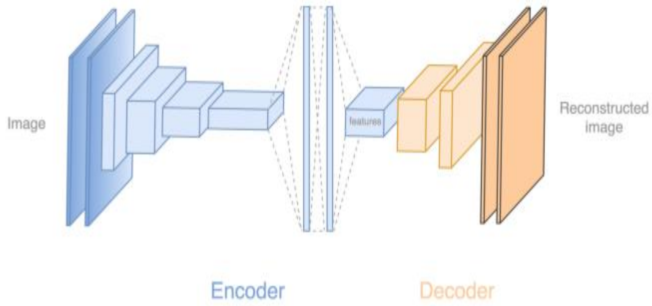

Fig-4: InceptionResNet V2

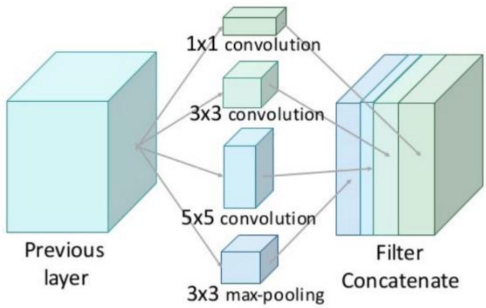

Fig-5: DeepFake generation

4 Literature Survey

The surge in the use of deepfake technology has fueled widespread apprehension due to its potential for malicious activities. To counteract this, deepfake detection has become a crucial area of research. While existing datasets like DeepfakeDetection and FaceForensics++ have significantly advanced detection methods, they often rely on videos with volunteer actors in controlled environments, limiting their representation of real-world scenarios. To address this gap, this paper presents the WildDeepfake dataset, encompassing 7,314 face sequences from 707 deepfake videos sourced entirely from the internet. In contrast to previous datasets, WildDeepfake aims to mirror the diversity and complexity of real-world deepfakes found online. The dataset's unique composition poses a more formidable challenge for deepfake detection algorithms, as it diverges from controlled settings and popular deepfake software. The authors conduct a comprehensive evaluation of foundation recognition systems across both traditional datasets and WildDeepfake, revealing the latter's increased difficulty and reduced detection performance. To enhance detection capabilities, the paper introduces two (ADDNets), leveraging attention masks on real and fake faces. The proposed ADDNets demonstrate empirical effectiveness not only on established datasets but crucially on the more demanding WildDeepfake dataset, reinforcing their potential for combating real-world deepfake threats. This research contributes to the ongoing development of robust deepfake detection mechanisms capable of addressing the evolving landscape of online deepfake content. This study introduces an innovative approach to deepfake detection by focusing on the consistency of source features within forged images. The underlying hypothesis posits that distinct source features can persist and be discerned even after undergoing advanced deepfake generation processes. The proposed method, termed pair-wise self-consistency learning (PCL), employs Convolutional Neural Networks (ConvNets) for representation learning, aiming to extract and identify these source features indicative of deepfake manipulation. Complementing PCL is a novel image synthesis technique known as the inconsistency image generator (I2G), which generates thoroughly labeled training datasets to facilitate the training of PCL. Through rigorous experimentation across seven prominent datasets, the models developed in this study exhibit notable improvements in deepfake detection. In the in-dataset evaluation, the average Area Under the Curve (AUC) increases from 96.45% to 98.05%, surpassing the current peak performance levels. Furthermore, in the cross-dataset evaluation, the AUC enhances from 86.03% to 92.18%. These results underscore the effectiveness of the suggested method, showcasing its capacity to improve the accuracy and reliability of deepfake detection models across diverse datasets. The research contributes valuable insights and methodologies to the ongoing efforts in fortifying defenses against the proliferation of deceptive deepfake content. In response to the formidable challenge posed by the proliferation of fake videos, particularly those generated by advanced generative adversarial networks, this paper introduces a novel approach for detecting deepfake videos. Leveraging the cutting-edge Attribution-Based Confidence (ABC) metric, the proposed method operates without the need for availability of training datasets or the adjustment model on validation datasets. Unlike traditional methods, the ABC metric enables inference solely based on the availability of the trained model. The methodology involves training a deep learning model exclusively on original videos, and subsequently employing the ABC metric to determine the authenticity of a given video. This metric generates confidence values, and for original videos, it establishes a threshold with confidence values exceeding 0.94. The utilization of the ABC metric provides a streamlined and efficient means of discerning between genuine and manipulated videos, presenting a promising avenue for deepfake detection without the necessity of accessing extensive training or validation datasets. This paper's contribution lies in its innovative application of the ABC metric, showcasing its effectiveness in distinguishing between authentic and deepfake videos. By focusing on attribution-based confidence, this approach represents a valuable addition to the arsenal of tools aimed at mitigating the challenges posed by the rapid evolution of deceptive video manipulation techniques. Response to the escalating threat posed by highly realistic deepfake content generated by advanced technologies like Generative Adversarial Networks (GANs), this paper introduces DeepfakeStack, a robust deep ensemble-based learning technique for detecting manipulated videos. The proliferation of deepfake technology has given rise to numerous illicit applications, such as deceptive propaganda, cybercrimes, and political campaigns, emphasizing the critical need for effective countermeasures. DeepfakeStack leverages recent advancements in deep learning models to create a comprehensive solution for detecting manipulated multimedia. By combining a series of state-of-the-art classification models into an ensemble, DeepfakeStack forms an enhanced composite classifier. Experimental results demonstrate the superior performance of DeepfakeStack, outperforming other classifiers with an impressive accuracy of 99.65% and an AUROC (Area Under the Receiver Operating Characteristic) score of 1.0 in deepfake detection. These findings highlight the effectiveness of the proposed method and position DeepfakeStack as a promising tool for building real-time deepfake detectors, offering a robust defense against the misuse of hyper-realistic multimedia in various illicit activities. The research provides a significant contribution to the ongoing efforts in developing advanced technologies to counteract the escalating challenges associated with the deceptive manipulation of audio and video content.

5 Results and Comparison

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\textbf{Precision} = \frac{True\ Positive}{True\ Positive+False\ Positive}$$

$$\textbf{Recall} = \frac{TP}{TP+FN}$$

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{Precision}+\frac{1}{Recall}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

$$\textbf{Sensitivity} = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

Specificity = $\frac{\boldsymbol{True\ Negatives}}{\boldsymbol{True\ Negatives + False\ Positives}}$

The formula for the mean squared error is: **MSE** = $\frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} (\boldsymbol{Y_i} - \widehat{\boldsymbol{Y}}_{\boldsymbol{i}})^{\mathbf{2}}$

MSE = Mean squared error, **n** = Number of data points, $\boldsymbol{Y_i}$ = Observed values, $\widehat{\boldsymbol{Y}}_{\boldsymbol{i}}$ = Predicted values

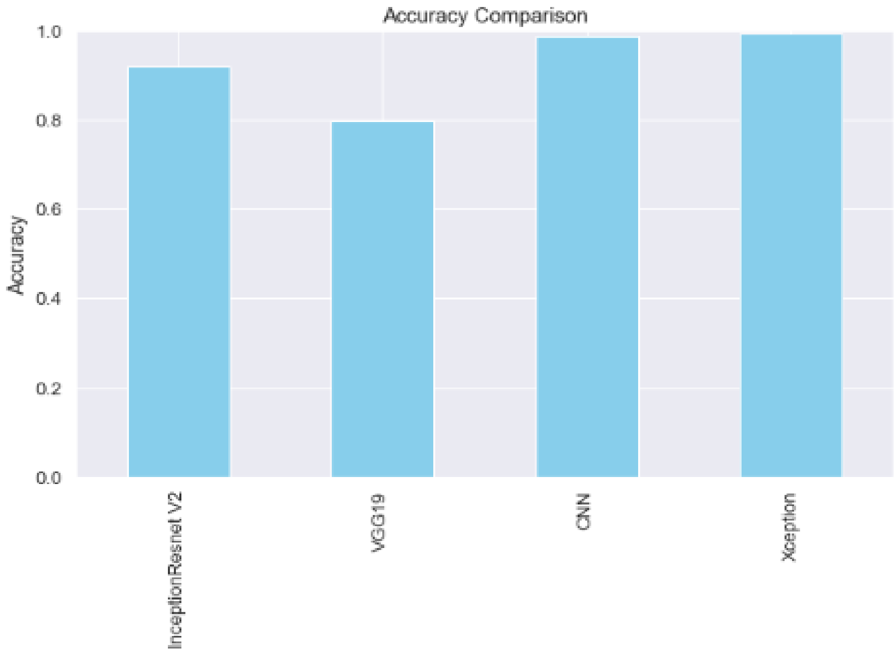

Fig-6: Accuracy comparison graph

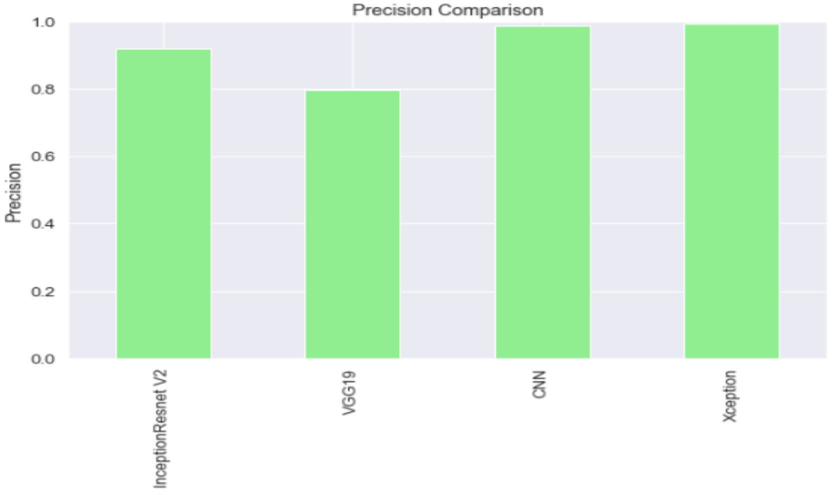

Fig-7: Precision comparison graph

Fig-8: Recall comparison graph

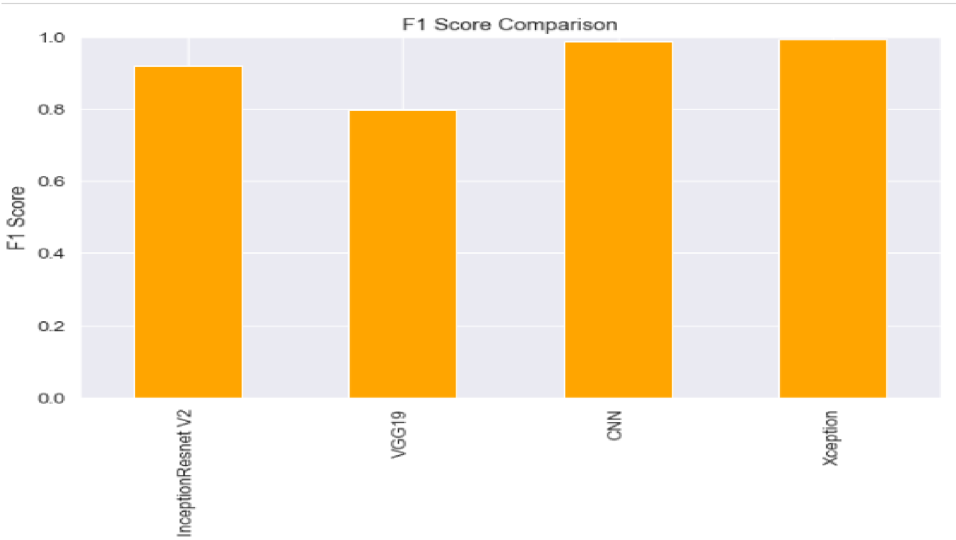

Fig-9: F1Score comparison graph

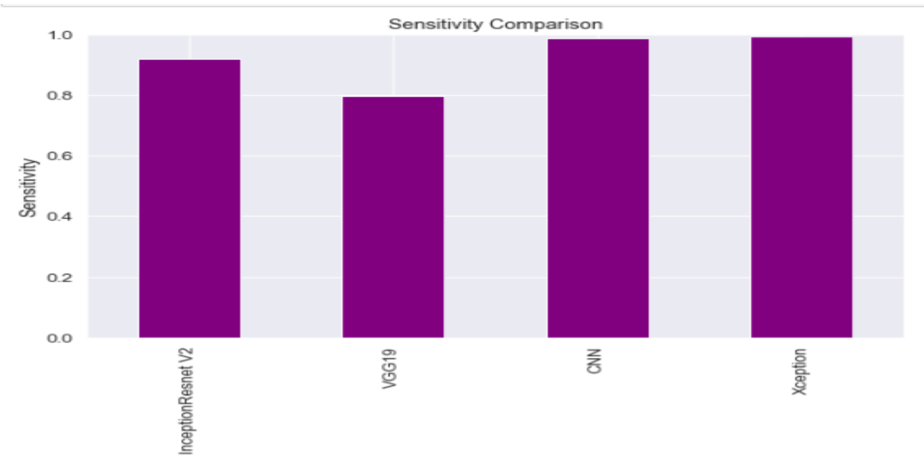

Fig-10: Sensitivity comparison graph

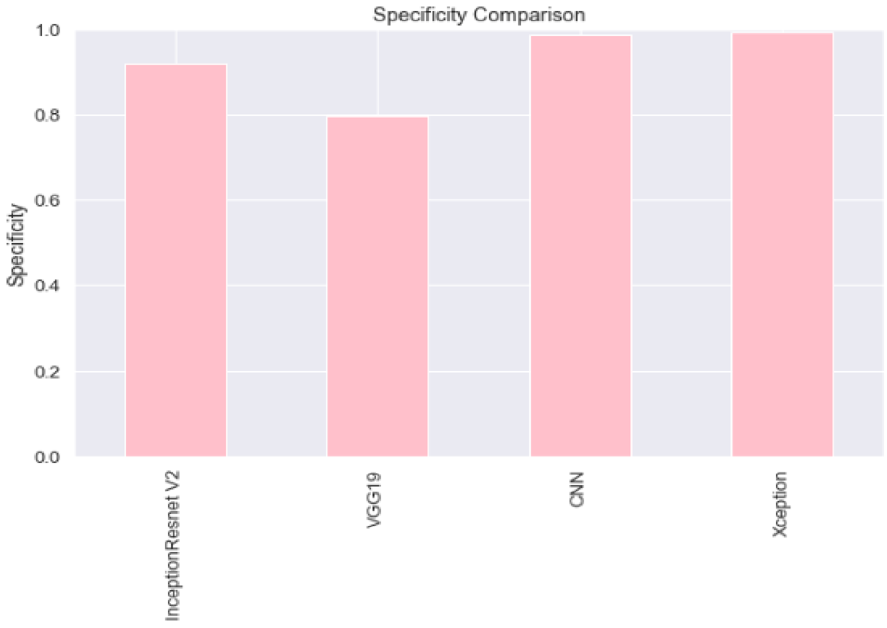

Fig-11: Specificity comparison graph

	Accuracy	Recall	Precision	F1 Score	Sensitivity	Specificity	MAE	MSE
InceptionResnet V2	0.918432	0.918415	0.918415	0.918415	0.918415	0.918415	<function mae at 0x00000204027E2288>	<function mse at 0x00000204027E23A8>
VGG19	0.796416	0.796435	0.796435	0.796435	0.796435	0.796435	0.32427	0.162385
CNN	0.987048	0.987036	0.987036	0.987036	0.987036	0.987036	0.019514	0.009877
Xception	0.993900	0.993902	0.993902	0.993902	0.993902	0.993902	0.009542	0.004718

Fig 12 Performance evaluation table

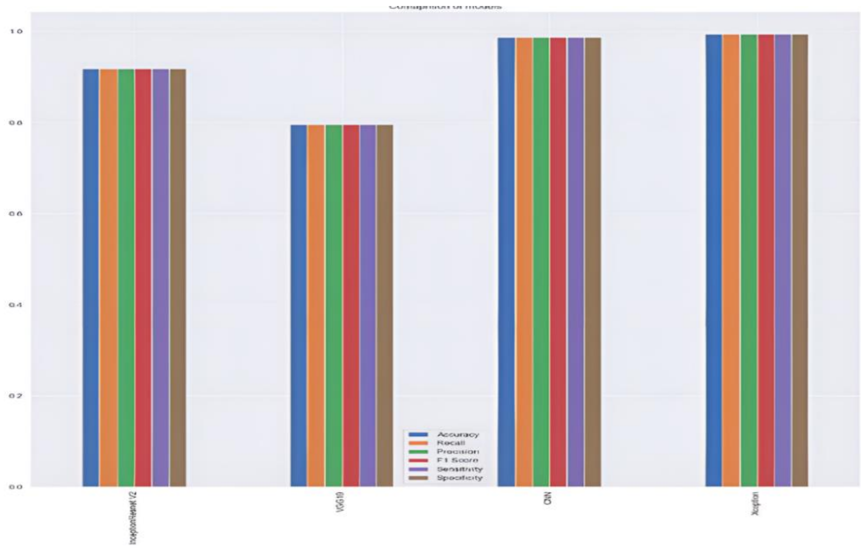

Fig-13: Performance evaluation comparison graph

6 Conclusions

In conclusion, this study underscores the imperative to evolve deep fake detection systems amid the rising sophistication of manipulative technologies. The existing system, while exploring classic and contemporary methods, reveals limitations in adapting to emerging threats and understanding intricate patterns. Recognizing these shortcomings, the proposed system takes a proactive stance, integrating cutting-edge algorithms such as InceptionResnetV2 and Xception. The use of a Kaggle deep fake dataset ensures a diverse training ground, enhancing the system's adaptability to real-world scenarios. By prioritizing a holistic approach, the proposed system not only aims to improve detection accuracy but also strives to deepen insights into the production and distribution dynamics of deep fakes. This comprehensive understanding is crucial for effective countermeasures against the potential societal ramifications of manipulated content, including fake news, privacy violations, and impersonations. The proposed system stands as a pivotal step toward fortifying our digital landscape against the malevolent misuse of deep fake technology, contributing to a more secure and resilient digital environment for users worldwide.

7 Future Work

The future scope of this research lies in continual advancements to counter emerging deep fake threats. Further exploration of innovative algorithms and the integration of evolving technologies, such as reinforcement learning, could enhance detection capabilities. Collaborative efforts across academia, industry, and policymakers are crucial to developing standardized protocols for deep fake detection. Additionally, ongoing research could delve into real-time detection systems and the integration of explainability features to increase transparency and user trust in deep fake detection technologies.

8 References

[1] M. Mirza and S. Osindero, "Conditional generative adversarial nets," arXiv preprint arXiv:1411.1784, 2014.
[2] Y. Bengio, P. Simard, and P. Frasconi, "Long short-term memory," IEEE Trans. Neural Netw, vol. 5, pp. 157–166, 1994.
[3] I. Goodfellow, Y. Bengio, and A. Courville, Deep learning. MIT press, 2016.
[4] S. Hochreiter, "Ja1 4 rgen schmidhuber (1997)."long short-term memory"," Neural Computation, vol. 9, no. 8.
[5] M. Schuster and K. Paliwal, "Networks bidirectional reccurent neural," IEEE Trans Signal Proces, vol. 45, pp. 2673–2681, 1997.
[6] J. Hopfield et al., "Rigorous bounds on the storage capacity of the dilute hopfield model," Proceedings of the National Academy of Sciences, vol. 79, pp. 2554–2558, 1982.
[7] Y. Wu, M. Schuster, Z. Chen, Q. V. Le, M. Norouzi, W. Macherey, M. Krikun, Y. Cao, Q. Gao, K. Macherey, et al., "Google's neural machine translation system: Bridging the gap between human and machine translation," arXiv preprint arXiv:1609.08144, 2016.
[8] L. Nataraj, T. M. Mohammed, B. Manjunath, S. Chandrasekaran, A. Flenner, J. H. Bappy, and A. K. Roy-Chowdhury, "Detecting gan generated fake images using co-occurrence matrices," Electronic Imaging, vol. 2019, no. 5, pp. 532–1, 2019.
[9] B. Zi, M. Chang, J. Chen, X. Ma, and Y.-G. Jiang, "Wilddeepfake: A challenging real-world dataset for deepfake detection," in Proceedings of the 28th ACM international conference on multimedia, 2020, pp. 2382– 2390.
[10] Madhavi, K. Reddy, A. Vinaya Babu, A. Anand Rao, and S. V. N. Raju. "Identification of optimal cluster centroid of multi-variable functions for clustering concept-drift categorical data." In Proceedings of the International Conference on Advances in Computing, Communications and Informatics, pp. 124-128. 2012.
[11] J. Luttrell, Z. Zhou, Y. Zhang, C. Zhang, P. Gong, B. Yang, and R. Li, "A deep transfer learning approach to fine-tuning facial recognition models," in 2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA). IEEE, 2018, pp. 2671–2676.
[12] S. Tariq, S. Lee, H. Kim, Y. Shin, and S. S. Woo, "Detecting both machine and human created fake face images in the wild," in Proceedings of the 2nd international workshop on multimedia privacy and security, 2018, pp. 81–87.
[13] Kuraparthi, Swaraja, Madhavi K. Reddy, C. N. Sujatha, Himabindu Valiveti, Chaitanya Duggineni, Meenakshi Kollati, and Padmavathi Kora. "Brain Tumor Classification of MRI Images Using Deep Convolutional Neural Network." Traitement du Signal 38, no. 4 (2021).
[14] X. Xuan, B. Peng, W. Wang, and J. Dong, "On the generalization of gan image forensics," in Chinese conference on biometric recognition. Springer, 2019, pp. 134–141.