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Real-Time Deepfake Detection: Detailed Survey on Techniques and Evaluation

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***Abstract*— The expansion of powerful creation technologies brings immediate and effective deepfake composition as a direct concern to the soundness of video-conference mediums, and pre-existing analyzers, typically crafted using recorded datasets, fail within swift, lessened and contrasting setups normal of actual streaming. We put forward an advanced HCGAN model to study key frame aspects, as well as we pair this with a simple CNN-LSTM mechanism. That capture action alongside inconsistent subtle signals during fast time slots. The analyzer uses a team-based discriminator with DenseNet parts combined with MobileNet parts. Each of these is formed through contradicting elements and parallel tasks and sorting intents, and to ensure sensible practice, we use set thinning as well as quantization. After this, 8-bit refinement takes place in conjunction with distillation knowledge in order to get a tight student model suitable for on-site surmising. We test our plan through assorted metrics, and then on varied set options with a face focus and we expose vast profits in rightness. Cross set hardiness proves successful, with run times reaching great rates as shown and with lower times achieved using adjusted embedded sets. We also give detailed breakdown by use of Gradient tools with appraisal of contrasting firmness despite constant meddling and the planned setup has exactness and rate, plus decryption is provided to help in realistic pipeline authenticity across videoconferencing.**

***Keywords*— Deep fake detection, Deep conditional generative adversarial networks, Ensemble discriminators Deepfakes, Face Forgery, Real-Time Detection, Generative Adversarial Networks.**

I. Introduction

Deepfake tech has seen quick growth in recent years thanks to progress in generative models like autoencoders, GANs, and newer diffusion-based systems. These models can recreate realistic facial expressions, swap identities, or sync lip movements with high accuracy. This makes it harder to tell fake videos from real ones. While these tools help with creative content, entertainment, and accessibility, they
also bring up big social and ethical issues. People have used deepfakes to spread false info, make up evidence, sway political stories, and pretend to be others. This challenges how much we can trust digital content in our daily talks. [1]

As deepfakes get more convincing, we need reliable systems to spot them in real time. Many current deepfake detectors work well offline but can't keep up with real-world needs like live streams, video calls, content moderation, and security checks. Real-time settings bring their own challenges: models must work fast, handle compressed or noisy videos, and run on regular computers or small devices.

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By using the same dataset as a reference, we want to compare spatial temporal, frequency-based, transformer-driven, and lightweight designs in a shared real-time setting. [2]

This survey makes four main contributions. First, we offer a structured grouping that sorts current real-time detection methods by model types and processing approaches. Second, we give a targeted breakdown of methods tested on FaceForensics++ showing what they do well where they fall short, and how they work in practice. Third, we look at the roadblocks still holding back real-time use such as working across different datasets, handling compressed videos, hardware limits, and new tricks to fool the systems, we point out possible areas to research to help create the next wave of models that work fast, can explain themselves, stay secure, and keep up with new ways to fake videos. [3]

The rest of this paper follows a logical structure to help readers understand the topic. Section II explains the basics of how deepfakes are made and current ways to spot them. Section III gives a thorough look at the FaceForensics++ dataset and how it's used as a benchmark. Section IV talks about the big hurdles in detecting deepfakes in real-time. Section V looks at cutting-edge real-time methods. Section VI tests these methods using common metrics and compares their results. Section VII explores how these methods might work in the real world, while Section VIII points out their limits and unsolved problems. Section IX shines a light on promising areas to research, and Section X wraps up the paper.

II. Deepfake Generation and Detection: An Overview

Deepfake technology is based on evolving generative models and they push the visual realism to the limit. You should have the knowledge of detection systems and particularly real-time systems. You have to take a look at deepfake creation, and how the detection system attempts to find out these fakes. Over the years, techniques used to work on faces ranged from simple autoencoder pipelines to complex GANs, and also diffusion models. These systems make believable facial expressions, or identity swaps, as well as speech synced animations. Modern deepfake ways are able to change subtle elements like lighting and skin, as well as changes in the expression. That can make fake content much harder when one is distinguished from media. [4]

Early systems used primarily autoencoders. These models encoded plus reconstructed facial looks. Although those models provided face-swapping, results were often missing details and had obvious problems. The introduction of GANs changed the field greatly and the methods of GAN helps to make real frames by learning how to fool the discriminator. High quality textures, along with smooth changes and better facial blends occur. Variants did help with realism such as StyleGAN or Cycle GAN and re-enactment driven frameworks. They improved identity swapping or expression shifts also motion re-enacting with less visual inconsistencies. [5]

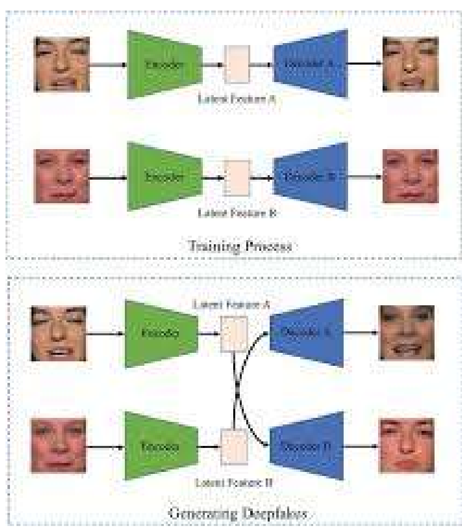

Fig. 1. Early deepfake generation architecture.

The deepfake models developed to be more complex, leading to detection. The old tricks were effective in the past when it comes to simple matters but not when it comes to deepfakes. The detection nowadays is based on data models and the models are models that examine clues in space or in time and spectra. CNNs are used to monitor frames and locate odd bits including textures or lights and boundaries by spatial detectors. Although it is suitable with clean data at high rate, it loses its performance when videos are squashed or tampered with. When analyzing sequences and finding hints like eye blinks, or brief glances, as well as motion that remains motionless, temporal techniques remedy the situation. Models are based on 3D CNNs, LSTMs or hybrids based on ConvLSTM. [6]

TABLE I. DEEPFAKE GENERATION TECHNIQUES

Method	Core Idea	Cost
Autoencoder	Face reconstruction	Low
GAN	Adversarial learning	High
DCGAN	CNN-based GAN	Medium
FaceSwap	Identity transfer	Medium
Face2Face	Expression reenactment	High
NeuralTextures	Neural rendering	Very High

A. DCGAN

Deep Convolutional GAN (DCGAN) is one of the first and most significant GAN architectures, which in both generator and discriminator introduced the idea of using fully convolutional layers. Instead of fully connected layers, which were the traditional way of creating GANs, DCGAN uses strided convolutions and batch normalization, thus enabling stable training and greatly enhancing the realism of the generated faces. The majority of the current deepfake generation methods, such as identity-swapping and attribute manipulation models, that use architectural principles of DCGAN as their backbone. As a result, DCGAN remains an indispensable reference to the deepfake generation lineage and a potent source for academic projects notwithstanding that DCGAN-produced frames can still have some artifacts when the resolution is high.

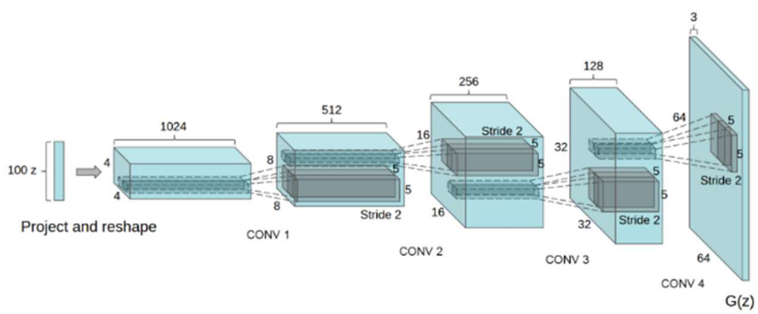

Fig. 2. DCGAN architecture typically used for generating synthetic facial images in deepfake

Beyond space plus time habits, other ways can check for how often images show, as GAN-made images have unique bits. These ways will reveal fake marks you might not find using vision. Multi-modal setups go further, as they include sound, plus bodily bits and even how parts link so things resist complex issues better. All told, those bits that find point to the nature of fakes, in which one tool isn't good, since it comes with perks for skill or speed and how sturdy that is plus how fast those run.

To see how deepfakes get done, plus the way bits see them show how real-time tasks pose a risk. The more things feel right and constraints go tight, the mix that happens in how things work in each end sets new deepfake research. [7]

III. THE FACEFORENSICS++ DATASET

The fast growth in deepfake studies has gained much help from large and strong datasets, and, in that group, FaceForensics++ has grown to become one widely used and great benchmark. Its size and varied ways of changes and well-planned judging steps make it a key mark for both school work and actual detection system growth. Knowing the dataset's parts and how it works is very important, because many live deepfake finders get training, tests, and get compared through this key mark. [8]

FaceForensics++ got made so as to have a full stock for looking at face changes under true to life states. It holds a number of clips changed using popular ways such as DeepFake, Face2Face, FaceSwap, and NeuralTextures, each causing kinds of twists and changes. What makes the dataset so useful is how it adds a number of squashing levels, from raw (c0) up to medium (c23) and very squashed (c40) videos. These transformations demonstrate what actually takes place where deepfakes circulate in message apps, social media locations, and streaming assistance, in most cases, with deplorable picture condition. Training and tests using these squash levels are important to be strong as live finders, in which the video received may not be guessable.

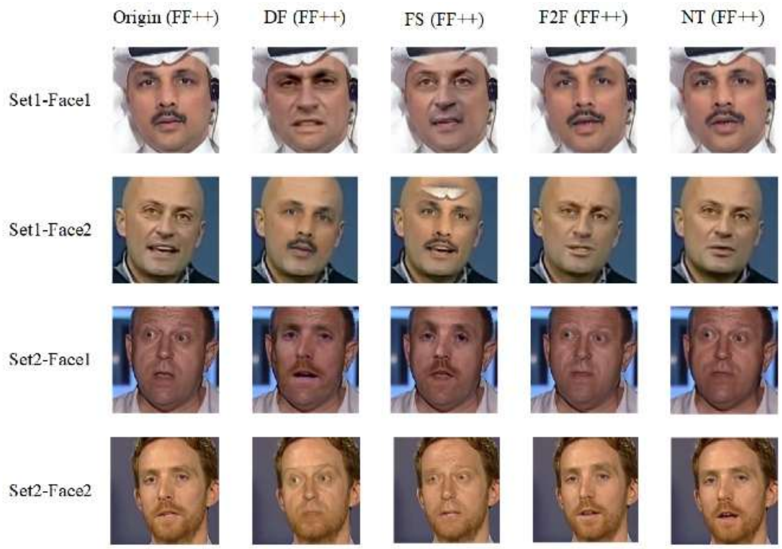

Fig. 3. Statistical summary of the FaceForensics++ dataset with real and manipulated samples

Another strong point for FaceForensics++ lies in its well-set train, test, and test cuts, which help fair looks among models. The dataset gives both clean and changed parts for each face, making sure that models learn how to tell real from fake and not learn face marks. Ground truth signs for change finders are given with care, and act is often judged by ways such as rightness, AUC, F1-score, and Equal Error Rate. These steps let those who study know not just the naming act but also how well a model holds up with changes in squash, light, and ways of changing. This care has let the dataset become the main test for much deepfake study books.

Though it is strong, FaceForensics++ has limits that those who study it must think of. As one case, the dataset is much made of set video clips with cared for spots, which may not fully show the hard part of true video. More than that, deepfake start ways have gone far since the dataset came out, so newer ways of changes—such as stream start clips and ways that use move tools—may not show well. There is as well the worry of dataset like: models that got long trains on FaceForensics++ often do great with the dataset but fight with cross-dataset moves when tried on datasets like Celeb-DF or DFDC. This gap points to how we still need more mixed and moving tests that show the present start techs. [9]

IV. Challenges in Real-Time Deepfake Detection

Although deepfake detection models have been shown to have achieved great improvement under the monitored conditions of a laboratory setting, implementing such type of systems in dynamic and real-time setting present a very different set of challenges altogether. Real-time processing must operate under strict latency constraints of the firm, random video quality, and various hardware limitations which is likely to make this task significantly more complex than offline processing. The realization of these problems proves to be essential to the development of models that will be considered reliable and feasible as far as practical applications in the real world, including social media regulation, video conferencing, live streaming, and even security surveillance, are concerned. [10]

Computational requirements remain a major challenge in deepfake detection, as high-performance models such as transformers, 3D CNNs, and multi-branch fusion networks require substantial processing power and storage. Running these models in real time, either frame-by-frame or sequence-based, can be computationally expensive, particularly on edge devices such as smartphones, tablets, and embedded systems. The trade-off between model size, inference speed, and detection accuracy remains a key concern. As a result, researchers are focusing on optimization techniques such as pruning, quantization, and lightweight architecture design to improve efficiency and enable real-time deployment.

TABLE II. SUMMARY OF REAL-TIME DEEPFAKE DETECTION CHALLENGES

Challenge Area	Description	Impact on Real-Time Detection
Computational Constraints	Deep models require high processing power and memory.	Slower inference, inability to run on mobile devices.
Model Complexity vs Accuracy Trade-off	Lightweight models lose precision; complex models are too slow.	Difficulty achieving both high accuracy and low latency.
Robustness to Compression and Noise	Real-world videos are often compressed (c23/c40), noisy.	Reduced performance due to loss of subtle visual artifacts.
Hardware Limitations	Devices vary in GPU/CPU capability, RAM, and thermal limits.	Inconsistent performance across platforms and failure on low-end devices.
Cross-Dataset Generalization	Models overfit to training datasets like FF++.	Poor performance on unseen datasets and new deepfake techniques.

Another issue will be the real trade-off between model complexity and accuracy of detection. A bigger model could include fined-grained visual in addition to time-based clues, but they do not always provide the responsiveness required in respect to real-time applications. Nevertheless, when it comes to quick inference, light-weight networks achieve that but may compromise durability- most prominently when exposed to the deepfakes generated with the state-of-the-art, state-of-the-art synthesis methods. And this pressure provides the need to make regular optimizations of architectures that can maintain solid performance despite remaining computationally viable.

And to make it worse, the additional complication is found with the robustness issues with reference to video compression, sound, and low-resolution input. Live-world platforms commonly scale back videos to decrease bandwidth and that smooths exterior many of the specific errors that detectors rely on. Models trained on both perfect and high-resolution images tend to collapse when challenged on massively compressed signals such as FaceForensics++ c23 and c40 levels, and when repeatedly trained on videos transmitted through messaging capabilities. Then the potential deficit of balance in the various quality levels position presents a significant challenge to reliable real-time. [11]

Cross-dataset generalization remains a major challenge, as models trained on popular datasets such as FaceForensics++ often struggle when tested on other datasets like DFDC and Celeb-DF, or under unseen manipulation techniques. This limitation arises because real-world videos vary significantly in lighting, background, recording conditions, and manipulation methods. Additionally, deepfake generation techniques evolve rapidly, introducing new artifacts that older detection models may fail to recognize. Ensuring that real-time detection systems can reliably handle unseen manipulations and diverse real-world conditions remains an important and ongoing research challenge. [12]

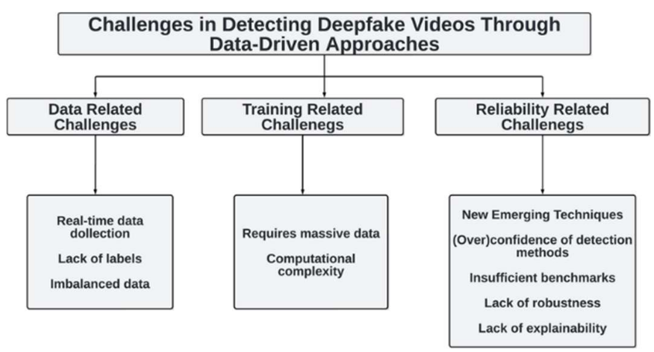

Fig. 4. Technical and computational challenges in deepfake detection.

V. SURVEY OF REAL-TIME DEEPFAKE DETECTION TECHNIQUES

A. Traditional Machine Learning Approaches

Traditional machine learning techniques were among the earliest approaches used for deepfake detection. These methods relied on handcrafted features extracted from facial regions, such as visual inconsistencies and structural artifacts. Classifiers like Support Vector Machines and Random Forests were commonly used due to their relatively low computational requirements. While these approaches were efficient, they showed limited performance against deepfakes generated using advanced GAN models. Their inability to capture complex feature representations reduces their effectiveness in modern real-time deepfake detection systems. [13]

B. CNN-Based Deep Learning Techniques

The growth in convolutional neural nets (CNNs) boosted counterfeit discovery greatly. Allowing styles to train on distinctive signs with no prepared info from organic movie frame pieces. Frameworks just like XceptionNet, MesoNet, EfficientNet, plus ResNet options break up signs in place of varying limits, construction blemishes, glow variety and pel idea. These styles show high correctness in datasets that were FaceForensics++ with better consequences with standard programs given wide spread amount of space. Numerous CNN based processes are quite CPU extensive, in spite of doing great which renders creating actual fast portable machine. Current studies attempted simplifying CNNs through getting rid of bad traits while additionally, there are other means for architectural basic alterations rendering more convenient moment sensitive sections. [14]

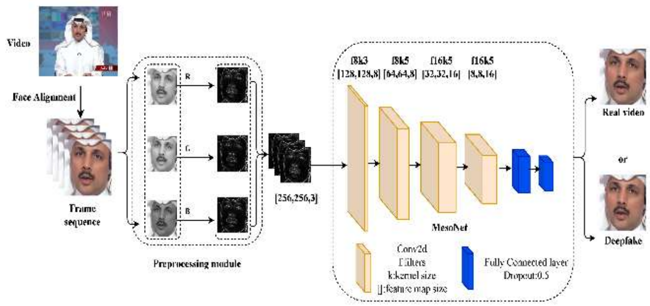

Fig. 5. Examples of CNN architectures used for deepfake detection

C. Temporal and Sequential Models

Temporal and sequential models enhance deepfake detection by analyzing frame-to-frame inconsistencies and motion patterns in videos. Techniques such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and 3D CNNs capture temporal dependencies, including unnatural facial movements, blinking patterns, and lip synchronization errors. These methods provide improved detection accuracy compared to single-frame analysis by incorporating temporal information. However, temporal models generally require higher computational resources and longer processing times, which can pose challenges for real-time applications. Efficient temporal modeling techniques are necessary to balance accuracy and performance.

D. Transformer-Based and Attention Mechanisms

Transformer founded spotting resources have newly captured consciousness given a capacity meant to draw together over many time spans or long lengths. Vision-Transformer versions, Swin Transformers and half-breed CNN-transformer pipeline using awareness to follow partnerships with location length and frame amount regions. Broad sense making may well give transformers the power to locate frail lack of harmony with emotion with moves in frame portions. Although it generally is known to show highly correct results in offline areas, they still call for plenty CPU source usages for focus uses. Using within speedy regions relies well with optimizations plus slim changing ways given parts. [15]

E. Multi-Modal and Audio-Visual Fusion Approaches

Sound plus view mix turns great with a road shown from a fault the sound can have while mixing with how words can show from the mouth. Various frameworks, or various ideas view all types of mouth signals plus audio stats shown that are unlike each other with the most. Ways may well use audio shown graphs plus voice embed to connect movement when it’s bad with wrong words. Once they give a great look that is found right now especially as audio from talk in-depth fakers need the amount plus how great the sounds shown are shown that increase while also adding delays into how fast areas react. [16]

TABLE III. DETECTION APPROACHES OVERVIEW

Category	Strength	Limitation
Traditional ML	Fast	Low accuracy
CNN	Spatial features	Heavy models
Temporal Models	Motion cues	High latency
Transformers	Global context	High cost
Lightweight CNNs	Real-time	Lower robustness
Multimodal	Higher accuracy	Complex setup

VI. EVALUATION METRICS AND PERFORMANCE ANALYSIS

A. Evaluation Metrics

To evaluate deepfake detection models we need useful evaluation metrics and in real-time scenarios we need things that capture both classification and computational performance. Typical things to measure, such as Accuracy or Precision or Recall or the F1-score, show general detection reliability, and using AUC-ROC helps provide insights into how well the model works if we have changing standards for accepting a fake. Also, the Equal Error Rate or EER helps for measuring biometric security and tells us when false positives are the same as false negatives. Real-time systems often need a measurement of latency and measurement of frames-per-second, or FPS, and knowing computational cost as FLOPS or GFLOPS will determine if you can use edge devices, as well as the best setups for sending data. [17]

B. Comparative Evaluation on FaceForensics++

Tests run on FaceForensics++ find that things like XceptionNet and EfficientNet models perform well on minimally processed data and the lightweight CNN models perform reasonably but don't need as much time. Experiments have found that image or video alteration will significantly affect the model ability to perform so having robust solutions should also address typical real-world processing concerns. Some results suggest if you know and track timing then it may outperform single-frame analysis when judging the material provided. [18]

C. Trade-Off Analysis: Accuracy vs Speed

Knowing real-time needs require that any model properly weighs things to maintain balance in relation to detection power while needing very little time to provide data. Really deep CNN models struggle with the requirements and will often not be able to produce between 25 to 30 frames-per-second when using commonly found consumer hardware, unless you quantize the data or take unnecessary parts out.. So, you must weigh this balance very heavily so you properly fit the deployment environment as well as device ability and things like power as well as overall streaming limits. [19]

VII. REAL-TIME IMPLEMENTATION SCENARIOS

A. Integration with Streaming and Social Media Platforms

Deepfake detectors are needed in social media networks or video streaming services and they should be the models that can handle large video streams at minimal latency. The flow of the content continuously implies that models facilitate the effective sampling of the frame, and it is required to have either a GPU acceleration or adaptive load balancing to ensure responsiveness. Other studies show that lightweight feature extractors co-optimize with streaming-beneficial inference pipelines and that this enhances the detection rates, and does not worsen the user experience. [20]

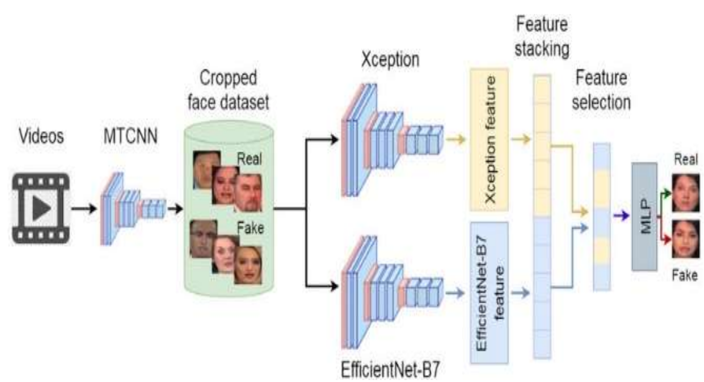

Fig. 6. Applications of deepfake detection systems in the real world

B. On-Device and Edge AI Deployment

Deployment on edge devices is demanded or systems are needed on smartphones and embedded systems so there must be compact models running without cloud reliance. Model quantization or pruning or efficient architectures and architectures like MobileNet, ShuffleNet, and transformer-lite variants let you get real-time inference even on low-power hardware and edge deployment enhances privacy and this can reduce network dependency.

C. Security Applications and Forensic use-Cases

The sectors of law-enforcement or cybersecurity depend on real-time detection when doing identity verification or authentication or for forensic video analysis. For these scenarios, there is a need for robustness to adversarial disturbances or compression artifacts or low-quality footage. If systems involve multi-modal fusion, along with audio-visual cross-verification, they'll display strong applicability in forensic settings. [21]

VII. FUTURE SCOPE AND CONCLUSION

Future research should focus on developing lightweight and efficient deepfake detection models suitable for real-time deployment on edge and resource-constrained devices. Improving robustness against adversarial attacks and enhancing generalization across diverse datasets remain critical challenges. Techniques such as optimized convolutional neural networks, efficient transformer architectures, and domain adaptation methods can improve detection reliability. Additionally, incorporating explainable AI approaches can enhance transparency, interpretability, and trust in deepfake detection systems. [22]

This paper presented a comprehensive survey of real-time deepfake detection techniques using the FaceForensics++ benchmark. Various detection approaches, including spatial CNN-based models, temporal analysis methods, transformer architectures, and multimodal fusion techniques, were analyzed in terms of detection accuracy and real-time feasibility. While significant progress has been achieved, challenges such as computational efficiency, compression robustness, and cross-dataset generalization still persist. Continued research focusing on efficient, scalable, and robust detection models will be essential for ensuring reliable real-time deepfake detection in practical applications.

REFERENCES

[1] Jia Deng, Gaoyang Pang, Zhiyu Zhang, Zhibo Pang, Huayong Yang, Geng Yang, cGAN based facial expression recognition for human-robot interaction, IEEE Access 7 (2019) 9848–9859.

[2] Candice R. Gerstner, Hany Farid, Detecting real-time deep-fake videos using active illumination, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 53–60.

[3] Hai Thanh Nguyen, Tinh Cong Dao, Thao Minh Nguyen Phan, Tai Tan Phan, Fake face detection in video using shallow, deep learning architectures, Int. J. Intell. Syst. Technol. Appl. 20 (6) (2022) 469–486.

[4] Ziyu Xue, Xiuhua Jiang, Qingtong Liu, Zhaoshan Wei, Global–Local facial fusion based GAN generated fake face detection, Sensors 23 (2) (2023) 616.

[5] Maryam Taeb, Hongmei Chi, Comparison of deepfake detection techniques through deep learning, Journal of Cybersecurity and Privacy 2 (1) (2022) 89–106.

[6] Zhimao Lai, Yufei Wang, Renhai Feng, Xianglei Hu, Haifeng Xu, Multi-feature fusion based deepfake face forgery video detection, Systems 10 (2) (2022) 31.

[7] Ammar Elhassan, Mohammad Al-Fawa'reh, Mousa Tayseer Jafar, Mohammad Ababneh, Shifaa Tayseer Jafar, DFT-MF: enhanced deepfake detection using mouth movement and transfer learning, SoftwareX 19 (2022) 101115.

[8] Zhiqing Guo, Gaobo Yang, Dewang Wang, Dengyong Zhang, A data augmentation framework by mining structured features for fake face image detection, Comput. Vis. Image Understand. 226 (2023) 103587.

[9] Shiming Ge, Fanzhao Lin, Chenyu Li, Daichi Zhang, Weiping Wang, Dan Zeng, Deepfake video detection via predictive representation learning, ACM Trans. Multimed Comput. Commun. Appl 18 (2s) (2022) 1–21.

[10] Shengqing Pei, Yu Wang, Bende Xiao, Shengchang Pei, Yaqi Xu, Yifan Gao, Jianbin Zheng, A bidirectional-LSTM method based on temporal features for deep fake face detection in videos, in: 2nd International Conference on Information Technology and Intelligent Control (CITIC 2022), vol. 12346, SPIE, 2022, pp. 311–318.

[11] Chongyang Zhang, Yu Qi, Hiroyuki Kameda, Multi-scale perturbation fusion adversarial attack on MTCNN face detection system, in: 2022 4th International Conference on Communications, Information System and Computer Engineering (CISCE), IEEE, 2022, pp. 142–146.

[12] Zhiqing Guo, Gaobo Yang, Dewang Wang, Dengyong Zhang, A data augmentation framework by mining structured features for fake face image detection, Comput. Vis. Image Understand. 226 (2023) 103587.

[13] Xinyi Ding, Zohreh Raziei, Eric C. Larson, Eli V. Olinick, Paul Krueger, Michael Hahsler, Swapped face detection using deep learning and subjective assessment, EURASIP J. Inf. Secur. (1) (2020) 1–12, 2020.

[14] K.H. Teoh, R.C. Ismail, S.Z.M. Naziri, R. Hussin, M.N.M. Isa, M.S.S.M. Basir, Face recognition and identification using deep learning approach, in: Journal of Physics: Conference Series, vol. 1755, IOP Publishing, 2021 012006, 1.

[15] Wei Liu, Jingdong Sun, General forgery face detection: against generative adversarial networks using knowledge distillation, in: 2022 5th International Conference on Data Science and Information Technology (DSIT), IEEE, 2022, pp. 1–5.

[16] Aditi Kohli, Abhinav Gupta, Light-weight 3DCNN for DeepFakes, FaceSwap and Face2Face facial forgery detection, Multimed. Tool. Appl. 81 (22) (2022) 31391–31403.

[17] Mohan Bhandari, Arjun Neupane, Saurav Mallik, Loveleen Gaur, Hong Qin, Auguring fake face images using dual input convolution neural network, Journal of Imaging 9 (1) (2022) 3.
[18] Junting Chen, Jiwen Dong, Qingtao Hou, Shenyuan Li, Xizhan Gao, Sijie Niu, Semi-supervised generative adversarial network for face anti-spoofing, in: The International Conference on Image, Vision and Intelligent Systems (ICIVIS 2021), Springer Nature Singapore, Singapore, 2022, pp. 121–130.
[19] Rahmat Ali, Young-Jin Cha, Attention-based generative adversarial network with internal damage segmentation using thermography, Autom. ConStruct. 141 (2022) 104412.
[20] B. Hariharan, S. Karthic, E. Nalina, PN Senthil Prakash, Hybrid deep convolutional generative adversarial networks (DCGANS) and style generative adversarial network (STYLEGANS) algorithms to improve image quality, in: 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), IEEE, 2022, pp. 1182–1186.
[21] Fiaz Majeed, Afzaal Ahmad, Muhammad Awais Hassan, Muhammad Shafiq, Jin-Ghoo Choi, Hamam Habib, Ontology-based crime news semantic retrieval system, CMC-COMPUTERS MATERIALS & CONTINUA 77 (1) (2023) 601–614.
[22] Tehseen Mazhar, Inayatul Haq, Allah Ditta, Syed Agha Hassnain Mohsan, Faisal Rehman, Imran Zafar, Jualang Azlan Gansau, Lucky Poh Wah Goh, The role of machine learning and deep learning approaches for the detection of skin cancer, in: Healthcare, vol. 11, MDPI, 2023, p. 415, 3.
[23] Tehseen Mazhar, Qandeel Nasir, Inayatul Haq, Mian Muhammad Kamal, Inam Ullah, Taejoon Kim, Heba G. Mohamed, Alwadai Norah, A novel expert system for the diagnosis and treatment of heart disease, Electronics 11 (23) (2022) 3989.
[24] https://doi.org/10.1109/ACCESS.2023.3343249.
[25] Qifeng Huang, Hanmiao Cheng, Kaijie Fang, Wenbin Yu, Cheng Fan, Yangsong Li, Non-intrusive load monitoring based on deep convolutional generative adversarial network prediction, in: 2022 IEEE 5th International Conference on Electronics Technology (ICET), IEEE, 2022, pp. 1050–1054.