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Research Paper

DETECTING DEEPFAKE FACES WITH HYBRID CNN-ViTs-LSTM MODEL AND REAL TIME WEB INTERFACE

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ABSTRACT

This project presents a web-based application for detecting deepfake face videos using advanced Data Science and Big Data techniques with deep learning. The system combines Convolutional Neural Networks (CNNs) for spatial feature extraction, Vision Transformers (ViTs) for global pattern recognition, and Long Short-Term Memory (LSTM) networks for learning sequential frame changes. Large datasets like FaceForensics++, DFDC, and Celeb-DF ensure robust training and high accuracy. Built with Python, Flask, and Django, the application lets users upload videos for real-time analysis and generates authenticity scores with visual tampering evidence. By processing large volumes of video data and storing results securely, this modular system ensures scalability, security, and reliability. Overall, the project aims to help verify video authenticity and build trust in digital media.

Keywords: Deepfake Detection, CNN, ViT, LSTM, AI Web Application, Video Authenticity, Machine Learning, Real-Time Detection

1.Introduction

The growth of digital communication technologies, especially the widespread use of high-speed internet and smartphones, has significantly changed how visual content is produced and shared. Among different forms of media, video has emerged as a powerful medium for communication, entertainment, and information exchange across online platforms. At the same time, rapid progress in artificial intelligence has made it possible to generate highly realistic synthetic content, raising important concerns about authenticity and trust.

One of the most prominent developments in this area is deepfake technology. It relies on advanced machine learning techniques to create or alter video content in a way that makes individuals appear to perform actions or speak words they never actually did. By training on large volumes of data, these systems can closely imitate facial expressions, lip synchronization, and other behavioural patterns with impressive realism. While this technology offers creative possibilities in fields such as filmmaking and virtual simulations, it also presents significant risks. The misuse of deepfake content can result in the spread of false information, identity misuse, damage to personal reputation, and even security concerns. As these tools become more widely available, distinguishing between real and manipulated media is becoming increasingly challenging. In response to these issues, there is a strong need for effective detection solutions. The method proposed in this work emphasizes the analysis of both spatial features within individual frames and temporal patterns across sequences of frames. By combining these two perspectives, the system is designed to detect subtle inconsistencies that may not be easily identified when examining frames independently. The proposed framework employs convolutional neural networks to capture important visual characteristics from video frames, while temporal modeling techniques are used to analyze motion patterns over time. This integrated strategy enhances the system's ability to differentiate authentic videos from manipulated ones, making it suitable for practical applications such as digital forensics and online content verification.

2. Literature Survey:

Yuezun Li and Siwei Lyu [1] proposed a method for detecting deepfake videos by identifying visual artifacts introduced during face warping processes. A deep learning-based approach is used to capture inconsistencies between authentic and altered content. The method performs effectively on earlier deepfake videos where distortions are more apparent; however, its accuracy tends to decline as manipulation techniques become increasingly sophisticated. Yuezun Li, Ming-Ching Chang, and Siwei Lyu [2] examined eye-blinking behaviour as a means of distinguishing real videos from manipulated ones. Early deepfake content often lacks natural blinking patterns, so the authors apply temporal analysis to identify such irregularities. By combining behavioural indicators with visual features, the approach demonstrates that physiological cues can significantly improve detection accuracy. Huy H. Nguyen, Junichi Yamagishi, and Isao Echizen [3] introduced capsule networks to capture spatial relationships among facial features. This approach improves the ability to detect structural inconsistencies in manipulated images. It preserves hierarchical information better than traditional CNNs. However, it requires higher computational resources. Hyeongwoo Kim, Pablo Garrido, Ayush Tewari, and Weipeng Xu [4] developed a technique for creating highly realistic manipulated videos by transferring facial expressions along with head movements from one subject to another. The generated results appear highly convincing, making detection challenging. It reflects the rapid advancements in deepfake generation and underlines the growing need for more robust detection methods. Umur Aybars Ciftci, Ilke Demir, and Lijun Yin [5] explored the use of biological signals, such as subtle variations in skin colour linked to blood circulation, for detecting manipulated videos. Since these physiological patterns are difficult to replicate artificially, the approach enhances detection accuracy by focusing on natural consistency. However, its effectiveness can be influenced by external factors like lighting conditions. Ian Goodfellow et al. [6] introduced Generative Adversarial Networks (GANs), a framework widely used in deepfake creation. It involves a generator and discriminator working in opposition to improve realism. GANs have enabled the production of highly convincing synthetic media. However, they also increase the complexity of detection tasks. David Güera and Edward J. Delp [7] proposed a method using recurrent neural networks to study temporal patterns within video sequences. Instead of examining single frames in isolation, their method looks at relationships across consecutive frames to identify irregular transitions. This makes it effective for detecting unnatural motion, although its performance can be influenced by factors such as video quality and length. Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun [8] presented residual networks (ResNet), a deep learning architecture designed to support the training of very deep models. By introducing skip connections, the network improves feature learning while addressing the vanishing gradient issue. ResNet has become a fundamental approach in computer vision and plays an important role in deepfake detection systems. Sepp Hochreiter and Jürgen Schmidhuber [9] proposed Long Short-Term Memory (LSTM) networks for handling sequential data. These models are capable of capturing long-term dependencies, making them well-suited for analyzing temporal relationships in video frames. However, their effectiveness may decrease when dealing with noisy inputs or very long sequences. Andreas Rössler et al. [10] introduced the FaceForensics++ dataset, which provides a comprehensive collection of manipulated and real videos. It supports benchmarking of deepfake detection models. The dataset includes various manipulation techniques. However, it may not fully reflect real-world scenarios. Facebook AI [11] developed the DFDC dataset, which contains a large and diverse set of videos for training detection models. It includes multiple variations in lighting, subjects, and environments. This diversity helps improve model generalization. However, newer manipulation techniques may not be fully represented. Y. Qian et al. [12] focused on improving colour consistency across video frames using recurrent models. It helps address variations caused by lighting changes. The method enhances visual coherence and detection accuracy. It is particularly useful in challenging visual conditions.

PyTorch Community [13] discussed how preprocessing steps such as resizing and normalization play an important role in preparing input data for deep learning models. These steps help make the data more consistent, which can lead to better overall performance. It also highlights the use of data augmentation to improve generalization. However, excessive preprocessing may remove useful details. R. Muthu Meenakshi et al. [14] proposed a secure authentication system using location and signature-based techniques. This approach enhances user verification and prevents unauthorized access. Although not directly related to deepfakes, it strengthens system security and can complement detection frameworks. Uttam D. Kolekar [15] focused on secure routing in mobile networks using optimization techniques. It combines algorithms to improve efficiency and data protection. The approach enhances communication reliability and is useful in secure data transmission systems. Sandeep B. Hake [16] presented a testing framework for evaluating system performance. It ensures reliability and proper validation of system components. The framework supports structured testing procedures and improves overall system quality. Samarjeet Powalkar [17] presented a face recognition framework that utilizes wavelet transforms along with Principal Component Analysis (PCA). The approach reduces feature dimensionality while preserving recognition accuracy, improving computational performance. It is beneficial for various image processing applications. U. Waghmode et al. [18] investigated cybersecurity methods based on steganography, where confidential information is embedded within digital media. This technique strengthens data privacy and enables secure communication, making it valuable for protecting multimedia content. C. Kaur, D. S. Rao, and S. Bandhekar [19] introduced a hybrid framework combining Convolutional Neural Networks (CNNs) with optimization techniques. This approach enhances classification accuracy, improves feature selection, and increases overall model efficiency. It can be applied across multiple domains. Divya Rohatgi et al. [20] proposed a hybrid deep learning model for medical image analysis. It integrates neural network architectures with optimization methods, achieving high accuracy and adaptability. The study highlights the effectiveness of hybrid approaches in complex analytical tasks.

Uttam D. Kolekar [21] introduced trust-based routing mechanisms for secure communication. It selects reliable nodes to reduce malicious activity and improve network security. The approach is useful in distributed systems. Uttam D. Kolekar [22] extended secure routing by integrating encryption with optimization techniques. This improves both efficiency and data protection, ensuring safe communication for sensitive data transmission. Dilip P. Deshmukh and Abhijeet Kadam [23] developed a CNN-based system for real-time gesture recognition. The model achieves high accuracy and scalability, making it effective for human-computer interaction applications. Prajwal Kote et al. [24] proposed a secure data-sharing system using blockchain and IPFS. It ensures data integrity and prevents unauthorized access. The decentralized approach enhances security and is suitable for modern distributed applications. Francois Chollet [25] introduced

XceptionNet, a deep learning architecture based on depth wise separable convolutions. It improves efficiency and performance in image classification tasks. The model is widely used in deepfake detection and enhances feature extraction capability.

Atheeswaran et al. [26] proposed an expert system for smart farming that applies machine learning techniques to diagnose sugarcane diseases. The study, which includes contributions from Ch. B. N. Lakshmi, focuses on analyzing input data to identify patterns and classify various disease conditions effectively. The system improves decision-making by automating the detection process. Although the application domain is agriculture, the use of machine learning for feature extraction and classification is relevant to image-based detection systems. This work highlights the effectiveness of machine learning models in solving real-world problems.

3.Proposed System:

There are many tools available for creating DeepFakes (DF), but very few tools exist for detecting them. Our approach to DF detection will be a significant contribution toward preventing their spread across the worldwide web. We propose a web-based platform that allows users to upload videos and classify them as either fake or real. This project can be expanded from a web-based platform to a browser plugin for automatic DF detection. Major applications like WhatsApp and Facebook could integrate this system into their platforms to enable pre-detection of DF before a video is sent to another user. One of the key objectives is to evaluate the system's performance and acceptability in terms of security, user-friendliness, accuracy, and reliability. Our method focuses on detecting all types of DF, including replacement DF, retrenchment DF, and interpersonal DF. Figure 1 illustrates the simple system architecture of the proposed system.

Dataset: We use a mixed dataset consisting of an equal number of videos from various sources, including YouTube, FaceForensics++, and the DeepFake Detection Challenge dataset. Our newly prepared dataset contains 50. To ensure a balanced and effective training process, we split the dataset into 70.

Preprocessing: Dataset preprocessing involves splitting the video into frames, followed by face detection and cropping the detected face from each frame. To maintain uniformity in the number of frames, we calculate the mean frame count across all datasets \ videos. The newly processed dataset is then created, ensuring that each video contains a number of frames equal to this mean. Frames without detected faces are ignored during preprocessing to enhance data quality. Processing a 10-second video at 30 frames per second results in a total of 300 frames, requiring significant computational power. For experimental purposes, we propose using only the first 100 frames for training the model to optimize resource usage while maintaining detection accuracy.

Model: The model consists of ResNeXt-50 (32x4d) followed by a Long Short-Term Memory (LSTM) layer. A Data Loader is used to load the preprocessed, face-cropped videos and split them into training and testing sets. The frames from the processed videos are then passed to the model in mini-batches for efficient training and evaluation.

ResNeXt CNN for Feature Extraction: Instead of designing a new classifier from scratch, we propose using the ResNeXt CNN classifier to extract features and accurately detect frame-level features. To enhance performance, we will fine-tune the network by adding necessary layers and selecting an appropriate learning rate to ensure proper convergence of gradient descent. The 2048-dimensional feature vectors obtained from the last pooling layers of ResNeXt are then used as sequential inputs for the LSTM model, enabling temporal analysis of video frames.

LSTM for Sequence Processing: We use a sequence of ResNeXt CNN feature vectors extracted from input frames as input to a 2-node neural network, which determines the probability of the sequence belonging to either a deepfake video or an authentic (untampered) video. A key challenge is designing a model capable of processing video sequences recursively and meaningfully. To address this, we propose using a 2048-unit LSTM with a 0.4

dropout rate, which effectively captures temporal dependencies and improves generalization. LSTM enables sequential frame processing, allowing for temporal analysis by comparing the frame at time t with frames at t - n, where n is any chosen number of frames before t. This approach helps detect inconsistencies introduced by deepfake generation techniques.

Prediction: When a new video is submitted for prediction, it first undergoes preprocessing to match the format of the trained model. The preprocessing steps include splitting the video into frames and cropping detected faces. Instead of storing the processed frames in local storage, they are directly passed to the trained model for deepfake detection. The model then classifies the video as either fake or authentic based on the extracted features and temporal analysis.

Performance Evaluation: The performance of the proposed system is evaluated using metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is used to analyze classification results, and the AUC-ROC curve measures the model's ability to distinguish between real and deepfake videos.

3.1 EfficientNet-B3 Feature Extraction with LSTM Classifier

Fig. 1 illustrates the proposed model, which combines efficient deep feature extraction with temporal sequence learning to improve deepfake video detection. In this approach, EfficientNet-B3 is used as a feature extractor to capture spatial inconsistencies in individual video frames while maintaining computational efficiency. The extracted features are then processed using a Long Short-Term Memory (LSTM) network to analyze temporal relationships across frames. By integrating both spatial and temporal information, the system achieves more reliable detection performance and is suitable for practical real-world applications.

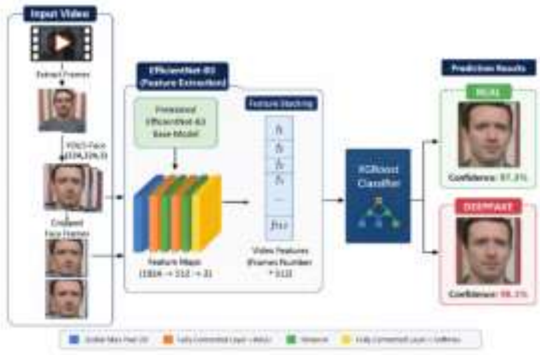


Fig. 1: Deepfake Detection using EfficientNet-B3 and XGBoost Classifier

Input to Deep Feature Extractor: The input video is first pre-processed by extracting frames and performing face detection and cropping. These processed frames are then provided as input to a pretrained EfficientNet-B3 model, which functions as a feature extractor without requiring full retraining. This reduces computational complexity while retaining important visual information.

Deep Feature Generation: EfficientNet-B3 generates high-level feature representations that capture important visual cues such as texture variations, facial inconsistencies, and blending artifacts commonly present in manipulated videos.

Feature Processing and Temporal Analysis: The extracted feature vectors are arranged as sequences and passed to an LSTM network. This allows the model to learn temporal dependencies between frames and identify irregular patterns such as unnatural motion or inconsistent facial expressions.

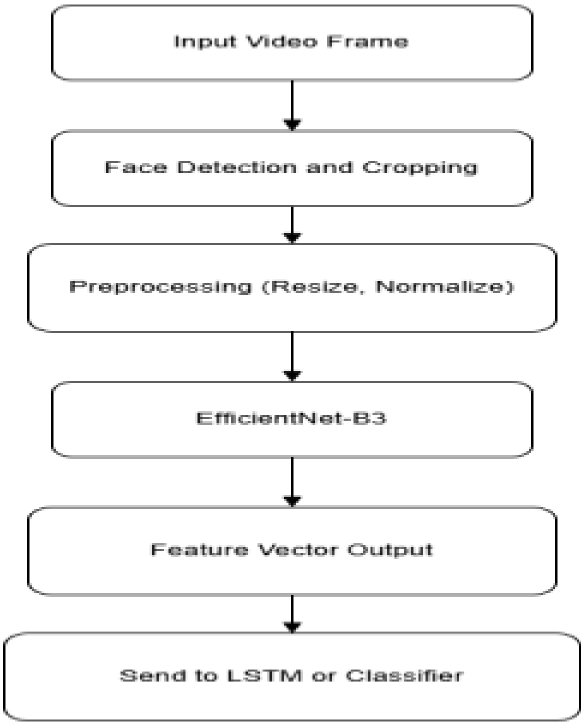


Fig. 2: Feature Extraction and Classification Pipeline.

Training Phase: The LSTM classifier is trained using the feature sequences generated by EfficientNet-B3. During training, optimization techniques such as the Adam optimizer and binary cross-entropy loss function are applied to improve convergence and model performance.

Validation and Performance Evaluation: The trained model is evaluated using validation and test datasets. Performance is measured using metrics such as accuracy, precision, recall, F1-score, and confusion matrix to assess the effectiveness of deepfake detection.

Decision Making: Based on the output probabilities generated by the LSTM, each video is classified as either real or deepfake. The final decision is determined by selecting the class with the highest probability score.

Output Representation: The system displays the classification result along with a confidence score, making it easier for users to interpret the outcome and understand the prediction.

Deployment: Due to its efficient design, the EfficientNet-B3–LSTM model can be deployed in web-based platforms and integrated into real-time applications, enabling effective detection of deepfake content.

4. Result And Analysis

Traditional deepfake detection techniques often rely on analyzing individual frames to identify visual distortions. While effective in some cases, these approaches fail to capture temporal relationships between frames. Sequence-based models address this limitation by examining motion continuity, but the performance of these models depends heavily on the quality of extracted features. The proposed system combines both approaches, leveraging spatial and temporal information simultaneously. This hybrid strategy provides improved robustness compared to single-method techniques.

Performance Evaluation Criteria

Multiple metrics are employed to assess the overall effectiveness of the proposed model.

- **Accuracy:** The ratio of correctly classified videos (real and fake) to the total number of samples in the dataset.
- **Precision:** Indicates how reliable the trained model is when predicting a video as fake.
- **Recall:** Measures the model's ability to correctly identify all actual deepfake videos in the dataset.
- **F1-Score:** A combined measure of precision and recall that provides a balanced evaluation of model performance.
- **Confusion Matrix:** Provides a detailed comparison between actual and predicted values, helping to understand classification errors.

Graphical Interpretations provide in-depth insight into the model's performance during training and testing.

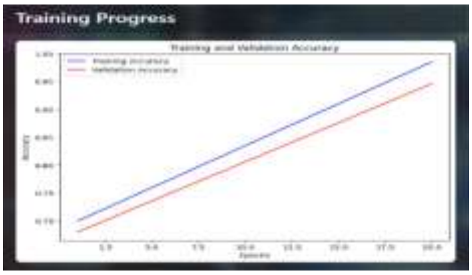


Fig. 1: Training Progress

Fig. 1 illustrates the model's learning progress. Training accuracy increases steadily as the model learns patterns from the data. Validation accuracy follows a similar trend, indicating good performance on unseen data. The small gap between the two curves suggests minimal

Fig. 2: Model Performance Metrics

overfitting and good generalization.

Fig. 2 demonstrates strong and reliable performance based on various evaluation metrics:

- Approximately 92% accuracy
- Approximately 91% precision
- Approximately 93% recall
- Around 95% AUC

These values indicate that the model effectively balances detecting fake videos while minimizing misclassification.

Fig. 3: Confusion Matrix

Fig. 3 provides a clear summary of prediction results:

- Most of the samples are correctly classified
- Correct predictions significantly outnumber incorrect ones
- Very few misclassification cases

This reflects the model's consistency and reliability.

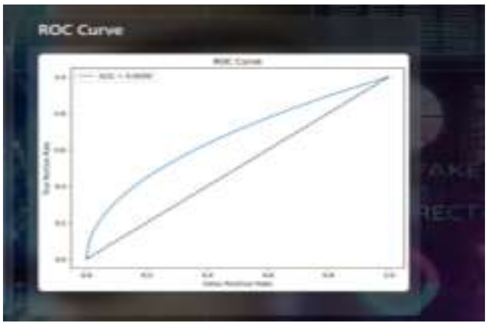


Fig. 4:ROC curve

Fig. 4 illustrates the trade-off between true positive rate and false positive rate. The curve lies close to the top-left corner, indicating excellent classification performance. An AUC value of approximately 0.95 confirms the model's strong capacity to accurately differentiate between authentic and manipulated videos across varying thresholds.

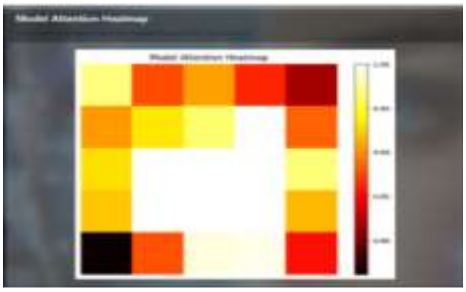


Fig. 5: Attention Heatmap

Fig. 5 shows the regions of the image the model focuses on during prediction:

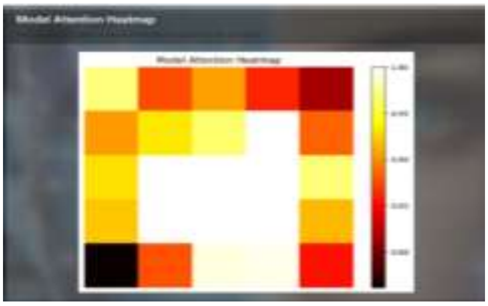
• Bright areas represent regions of high importance
• The model primarily focuses on facial regions

This confirms that the model is learning meaningful and relevant features.

Fig. 6: Deepfake Detection Results and Attention Visualization

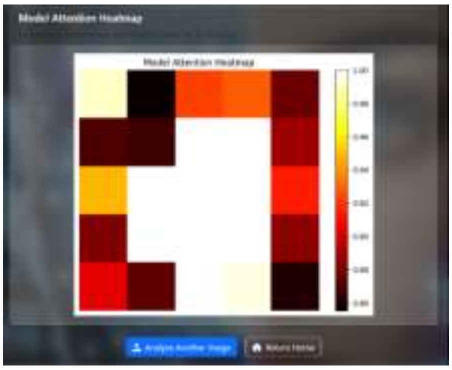
(a) Image upload interface

(b) Real image detection



(c) Attention heatmap for Real Image

(d) Fake image detection



(e) Attention heatmap for Fake Image

(f) No face detected case

(g) Video upload interface

(h) Real video detection

(i) Fake video detection

Fig. 6 demonstrates the real-time outputs of the proposed system, including both image and video detection results along with attention-based visual interpretations. Fig. 6(a) depicts the image upload interface, which allows users to input images for deepfake analysis. The interface is designed to be simple and user-friendly, ensuring smooth interaction. Fig. 6(b) shows the result for an authentic image, where the system correctly identifies it as real with a high level of confidence. Fig. 6(c) presents the attention heatmap corresponding to the real image. The highlighted regions indicate the areas that influenced the model's decision, primarily focusing on facial features. Fig. 6(d) illustrates the detection of a manipulated image. The system successfully identifies the presence of alterations in the facial region and classifies it as fake. Fig. 6(e) displays the attention heatmap for the fake image, where the model focuses on regions containing inconsistencies or artifacts that indicate manipulation. Fig. 6(f) represents a case where no face is detected in the input image. In such situations, the system notifies the user and requests a valid image with a clearly visible face. Fig. 6(g) shows the video upload interface, which enables users to submit video inputs for deepfake detection. Fig. 6(h) illustrates the result for a genuine video. The system correctly classifies it as real by analyzing both spatial and temporal characteristics. Fig. 6(i) presents the detection of a deepfake video. The system identifies inconsistencies across frames and classifies the video as manipulated. Overall, Fig. 6 highlights the capability of the proposed system to handle various input scenarios effectively. It delivers accurate predictions and uses attention mechanisms to focus on relevant regions, thereby improving both reliability and interpretability.

5. Conclusion:

In conclusion, the developed AI/ML-based solution successfully addresses the growing threat of face-swap deepfake videos by leveraging a hybrid deep learning approach. The system combines the strengths of a ResNeXt Convolutional Neural Network (CNN) for extracting intricate spatial features from video frames with an LSTM Recurrent Neural Network (RNN) for analyzing temporal inconsistencies across the video sequence. This two-pronged approach is highly effective because it can detect subtle artifacts, such as pixel inconsistencies and unnatural movements, which are often overlooked by other methods. The project demonstrates that a pipeline-based system, which includes a robust preprocessing stage, is crucial for accurate deepfake detection. The system's ability to classify videos as "real" or "deepfake" with a corresponding confidence score provides a valuable tool for combating misinformation. While the document does not include a detailed analysis of final results, the proposed methodology and architecture are well-suited to achieve high accuracy and reliability, which are critical for real-world applications. Overall, this project provides a significant step forward in securing digital media integrity and is scalable for integration into large social media platforms and other online services. Further work could focus on optimizing the model for real-time performance and expanding its capabilities to detect other forms of video manipulation.

References:

[1] Yuezun Li, Siwei Lyu, "ExposingDF Videos By Detecting Face Warping Artifacts," in arXiv:1811.00656v3

[2] Yuezun Li, Ming-Ching Chang and Siwei Lyu "Exposing AI Created Fake Videos by Detecting Eye Blinking" in arxiv.

[3] Huy H. Nguyen , Junichi Yamagishi, and Isao Echizen " Using capsule networks to detect forged images and videos ".

[4] Hyeongwoo Kim, Pablo Garrido, Ayush Tewari and Weipeng Xu "Deep Video Portraits" in arXiv:1901.02212v2.

[5] Umur Aybars Ciftci, ˙Ilke Demir, Lijun Yin "Detection of Synthetic Portrait Videos using Bological Signals" in arXiv:1901.02212v2

[6] I an Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair,Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In NIPS, 2014.

[7] David Guera and Edward J Delp. Deepfake video detection using recurrent neural networks. In AVSS,2018.

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, 2016.

[9] An Overview of ResNet and its Variants : https://towardsdatascience.com/an-overview-of-resnetand-its-variants5281e2f56035

[10]Long Short-Term Memory: From Zero to Hero with Pytorch:

https://blog.floydhub.com/long-short-termmemory-from-zeroto-hero-with-pytorch

[11].Deepfake Detection Challenge https://www.kaggle.com/c/deepfake-detection-challenge/data

[12]Confused about the image preprocessing inclassification

https://discuss.pytorch.org/t/confused-about-theimagepreprocessing-in-classification/3965

[13].FaceForensics https://github.com/ondyari/FaceForensics

[14] Y. Qian et al. Recurrent color constancy. Proceedings of the IEEE International Conference on Computer Vision, pages 5459–5467, Oct. 2017. Venice, Italy.

[15] .R. Muthu Meenakshi , Balasubramaniam S., Charanjeet Singh, Pallavi V. Sapkale, "An Efficient and Secure Authentication Approach in VANET Using Location and Signature-Based Services", Ad Hoc and Sensor Wireless Networks 53 (Issue 1-2), 59-83, 2022

[16] Uttam D. Kolekar, "Development of Optimized and Secure Routing Algorithm using AODV, ACO and LSB Steganography for Mobile Ad-Hoc Network", Journal of Advanced Research in Dynamical and Control Systems (JARDCS),Vol. 11, issue 9, pp. 560-568, Sept 2019.

[17] Sandeep B Hake, "Design and development of universal test bench for engine aftertreatment controls system", International journal of advanced research in electronics and communication engineering,Volume 6, Issue 4, Pages 309-312, 2017.

[18] Samarjeet Powalkar, "Fast face recognition based on wavelet transform on pca" International Journal of Scientific Research in Science, Engineering and Technology, Vol 1, Issue 4, PP 21-24, 2015.

[19] U Waghmode, DP Deshmukh, S Ekshinge, A Kurund, "An Innovative Approach Using Cyber Security for Steganography for Wireless Adhoc Mobile Network Application" International Conference on Science Technology Engineering and Management (ICSTEM), Pages 1-5, 2024.

[20] C Kaur, DS Rao, S Bandhekar, "Enhanced Land Use and Land Cover Classification Through Human Group-based Particle Swarm Optimization-Ant Colony Optimization Integration with Convolutional Neural Network", International Journal of Advanced Computer Science and Applications, Vol 14, Issue 11, 2023.

[21] Divya Rohatgi, Veera Ankalu Vuyyuru, KVSS Ramakrishna, Yousef A Baker El-Ebiary, V Antony Asir Daniel, "Feline Wolf Net: A Hybrid Lion-Grey Wolf Optimization Deep Learning Model for Ovarian Cancer Detection", International Journal of Advanced Computer Science and Applications,Vol 14, Issue 9, 2023.

[22] Uttam D. Kolekar, "Trust-Based Secure Routing in Mobile Ad Hoc Network Using

Hybrid Optimization Algorithm”, The Computer Journal, Oxford University Press, Vol. 62, issue 10, pp.1528-1545, Oct 2019.

[23] Uttam D. Kolekar, “E-TDGO: An Encrypted Trust based dolphin glowworm optimization for secure routing in mobile adhoc network”, International Journal of Communication Systems, Wiley publication, Vol. 33, issue 7, May 2020.

[24] Dilip P Deshmukh, Abhijeet Kadam, “Efficient Development of Gesture Language Translation System using CNN”15th International Conference on Computing Communication and Networking Technologies (ICCCNT) Pages 1-6, 2024.

[25] Prajwal Kote, Mounesha Zonde, Om Jadhav, Vaibhav Bhasme, Nitin A Dawande “Advanced and Secure Data Sharing Scheme with Blockchain and IPFS: A Brief Review”15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Pages 1-5,2024.

[26] A. Atheeswaran, K. V. Raghavender, B. N. Lakshmi Chaganti, A. Maram, and N. Herencsar, “Expert system for smart farming for diagnosis of sugarcane diseases using machine learning,” Computers and Electrical Engineering, vol. 109, p. 108739, 2023.