Smt. Kamala & Sri Venkappa M. Agadi College of Engineering & Technology,Lakshmeshwar-582116
(Approved by AICTE ,New Delhi & Affiliated to VTU Belagavi, ISO 9001:2015 Certified)
Department of Information Science and Engineering

"Deep Fake Video Detection"

Using Deep Learning

Under the Guidance of
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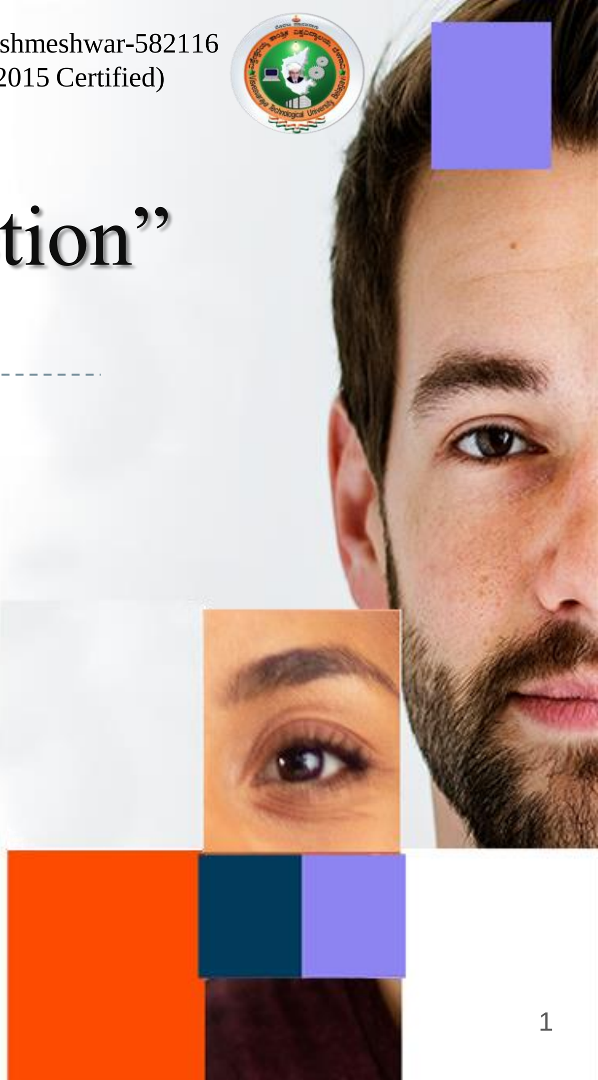
FINAL YEAR STUDENTS
INFORMATION SCIENCE ENGINEERING
SKSVMACET-LAXMESHWAR



CONTENTS

INTRODUCTION

- DEEP FAKE - A Deep fake is a machine learning generated image or video that has been manipulated to misrepresent someone.

- DEEP LEARNING - Deep learning is a branch of machine learning that concentrates on CNN.

- DEEP FAKE VIDEO DETECTOR - is a sophisticated tool designed to identify manipulated videos created through advanced technological means

LITERATURE SURVEY

	Year	Author	Topic	Techniques Used	Limitation
01	2020	Nikita S, Anton V	Combining Deep Learning and Super-Resolution Algorithms for Deep Fake Detection	**Inconsistent Head Pose Analysis & CNN ResNet50 Model**	▪ **Accuracy** ▪ **Scalability** ▪ **Ethical Implications**
02	2022	Aditya Jagtap, Saloni Sharma	Synthetic Content Detection in Deepfake Video using Deep Learning	**Convolutional Neural Networks (CNN) & Long Short-Term Memory (LSTM).**	▪ **Scope** ▪ **Real-time Detection** ▪ **Robustness**
03	2023	Fahad Mira	Deep Learning Technique for Recognition of Deep Fake Videos…	**Lip-Syncing and Neural Networks, Artificial Neural Networks, Cyber Secure.**	▪ **Data Dependency** ▪ **Detection Challenges** ▪ **Speed and Efficiency**

PROBLEM STATEMENT

- Why Deep Fake Detection **?**
- Can we detect Deep fakes with naked eyes **?**

❑ Why Deep Fake Detection ?

- ✓ Fake News
- ✓ Financial fraud
- ✓ Celebrity unusual video
- ✓ Revenge porn
- ✓ Politician videos

❑ Can we detect Deep fakes with naked eyes?

RESULT

OBJECTIVES

- To identify manipulation content .
- To develop Robust Detection Models.
- To perform Metrics Definition .
- To preserves Authenticity and Enhancing Cybersecurity .

Some of machine learning algorithms and computer vision techniques to achieve the above objectives are:

1]CNN	2] LSTM
3]ResNext	4]RNN

SYSTEM SPECIFICATIONS

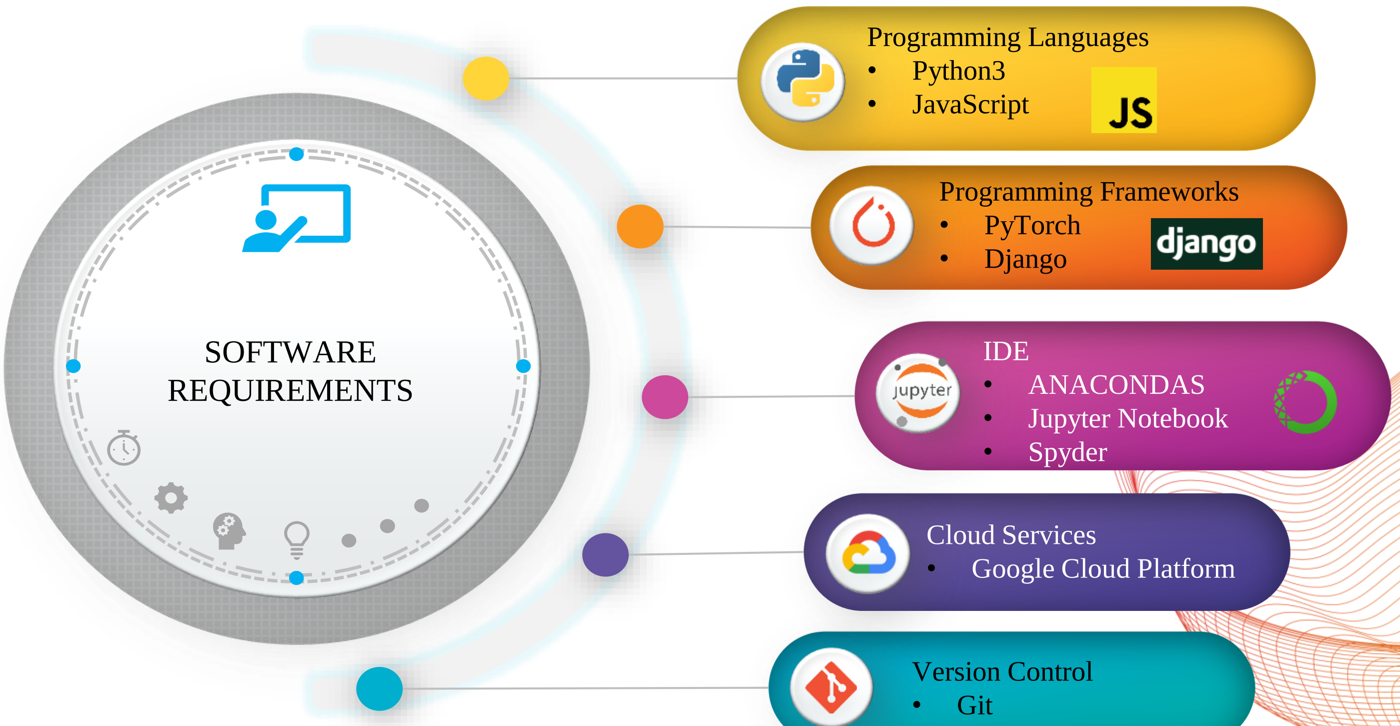
FUNCTIONAL SPECIFICATIONS

- Video Input Handling.
- Deepfake Detection Model.
- Dataset Integration.
- Real-time Processing.
- Model Evaluation.

NON FUNCTIONAL SPECIFICATIONS

- Performance.
- Accuracy.
- Scalability.
- Reliability.

SYSTEM REQUIREMENTS

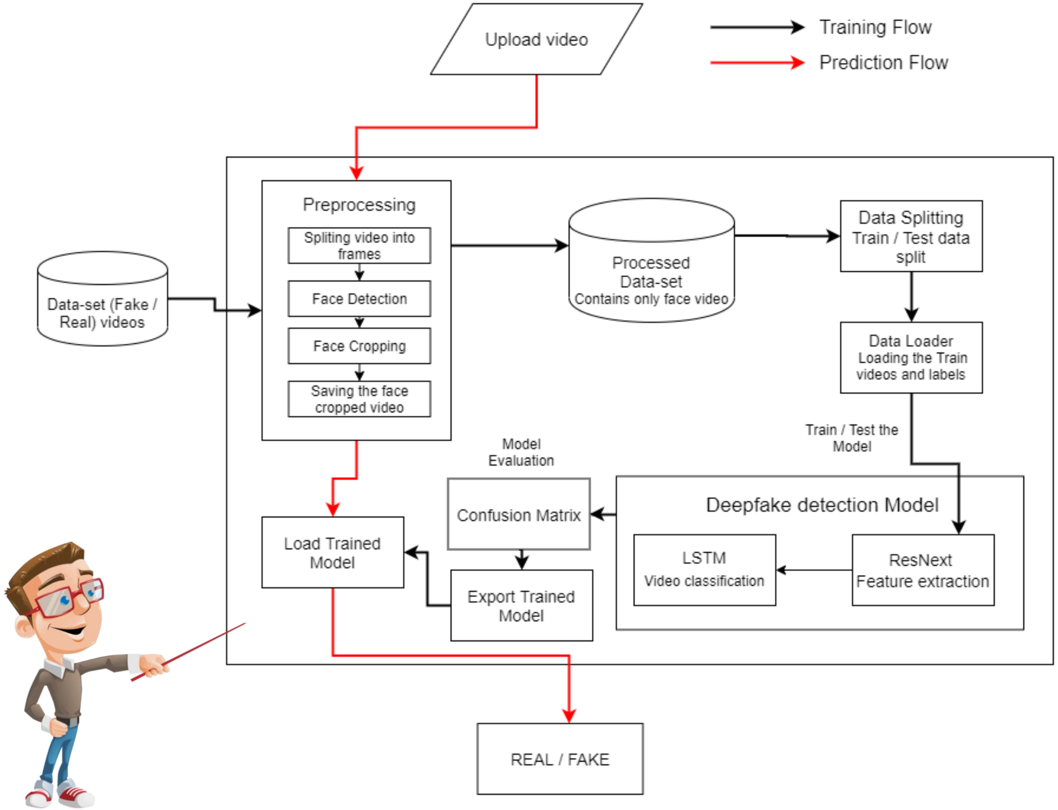


HARDWARE REQUIREMENTS

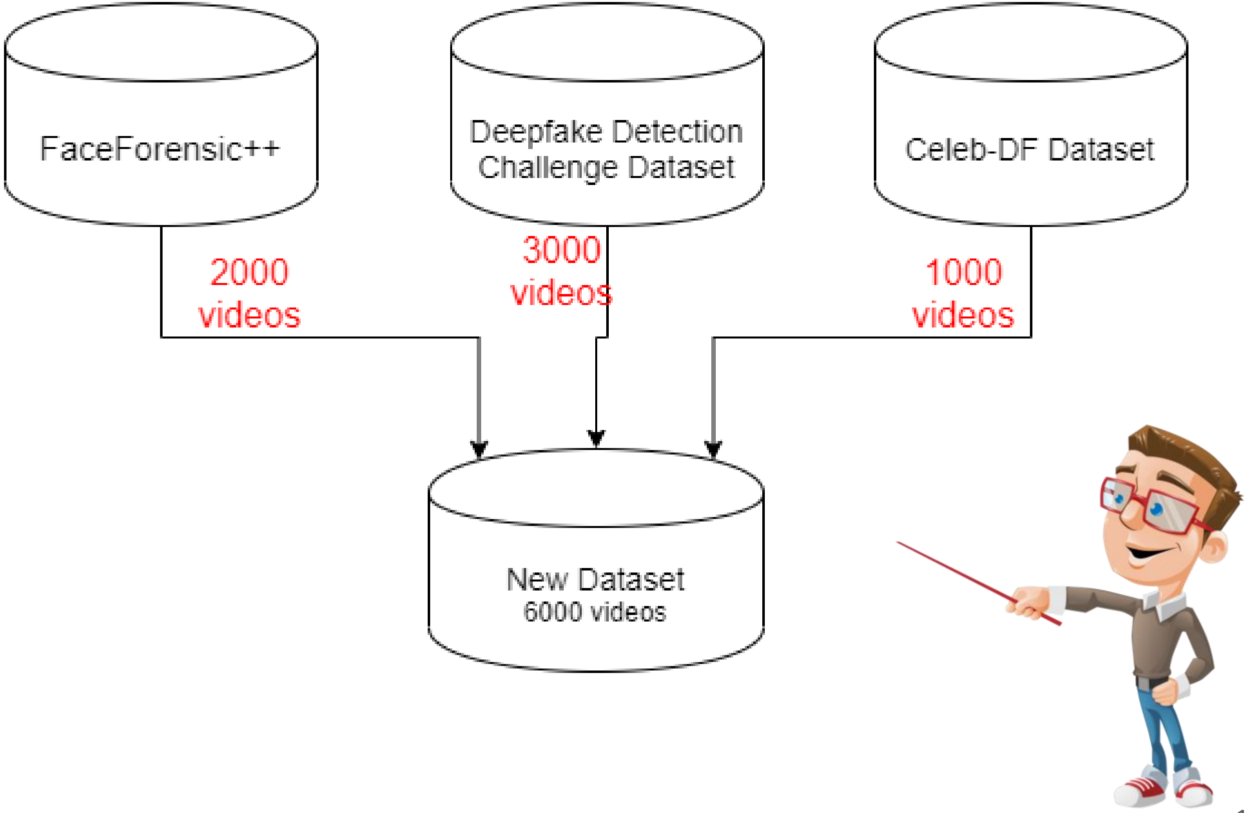
- CPU (Central Processing Unit)
  - Intel Core i5 or higher
- RAM (Random Access Memory)
  - 16GB or 32GB
- GPU (Graphics Processing Unit)
  - NVIDIA GeForce Rtseries
- Storage (Hard Disk)
  - 64GB or 128GB

METHODOLOGY

System Architecture

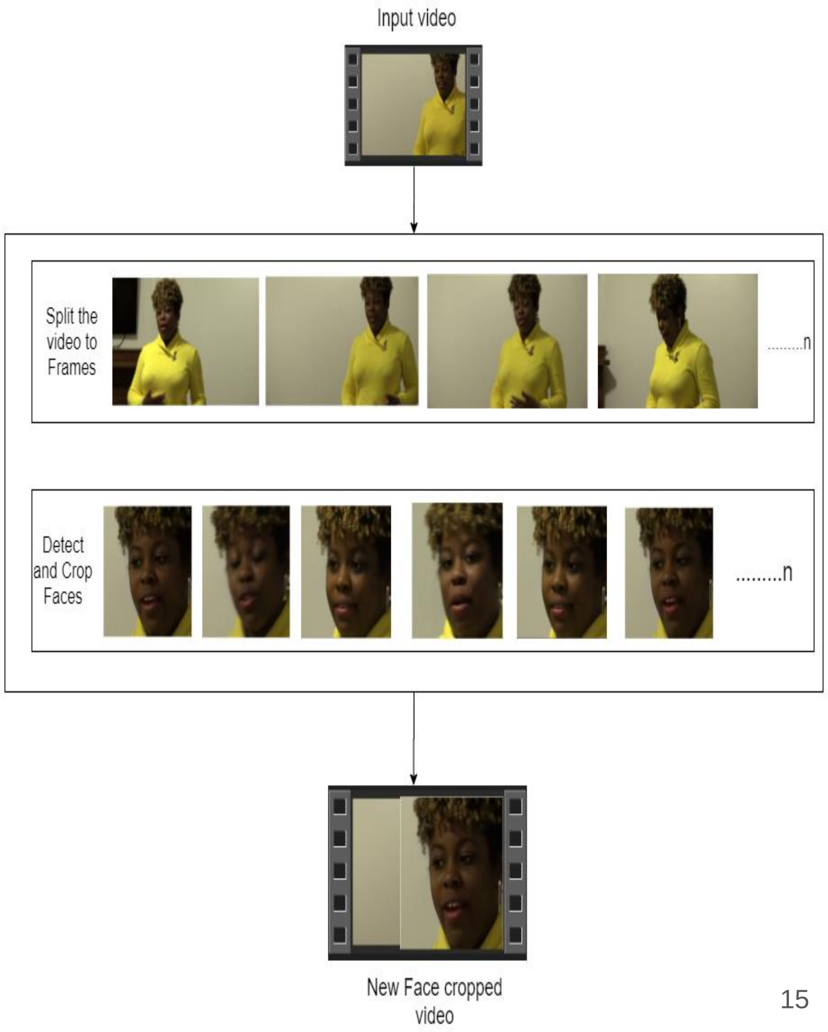


Data-set Exploration



Pre-processing

1. SPLIT VIDEO INTO FRAMES
2. FACE DETECTION
3. CROPING FACE
4. CREATING NEW FACE CROPPED VIDEO
5. SAVING THE FACE CROPPED VIDEO



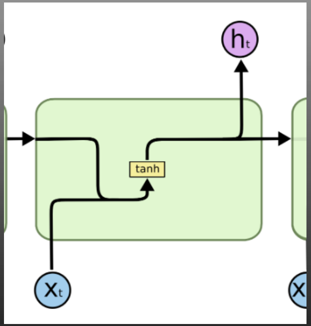
Model Architecture

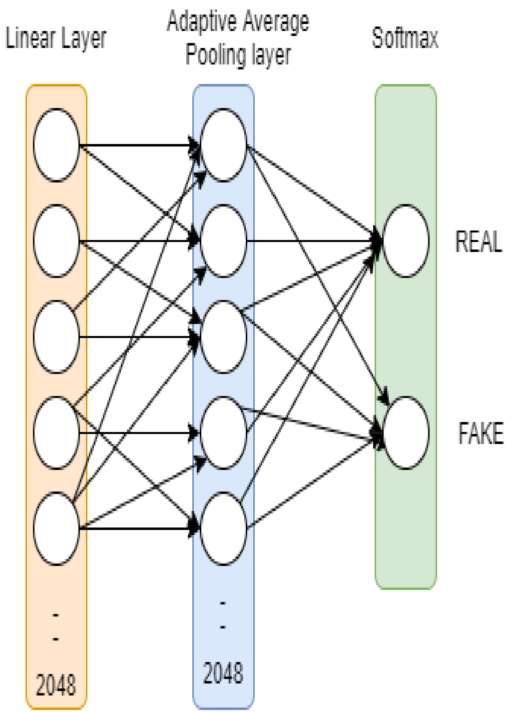
ResNext-50

stage	output	ResNeXt-50 (32×4d)	
conv1	112×112	7×7, 64, stride 2	
conv2	56×56	3×3 max pool, stride 2	
		[1×1, 128 3×3, 128, C=32 1×1, 256]	×3
conv3	28×28	[1×1, 256 3×3, 256, C=32 1×1, 512]	×4
conv4	14×14	[1×1, 512 3×3, 512, C=32 1×1, 1024]	×6
conv5	7×7	[1×1, 1024 3×3, 1024, C=32 1×1, 2048]	×3
	1×1	global average pool 1000-d fc, softmax	
# params.		**25.0**×10^6	

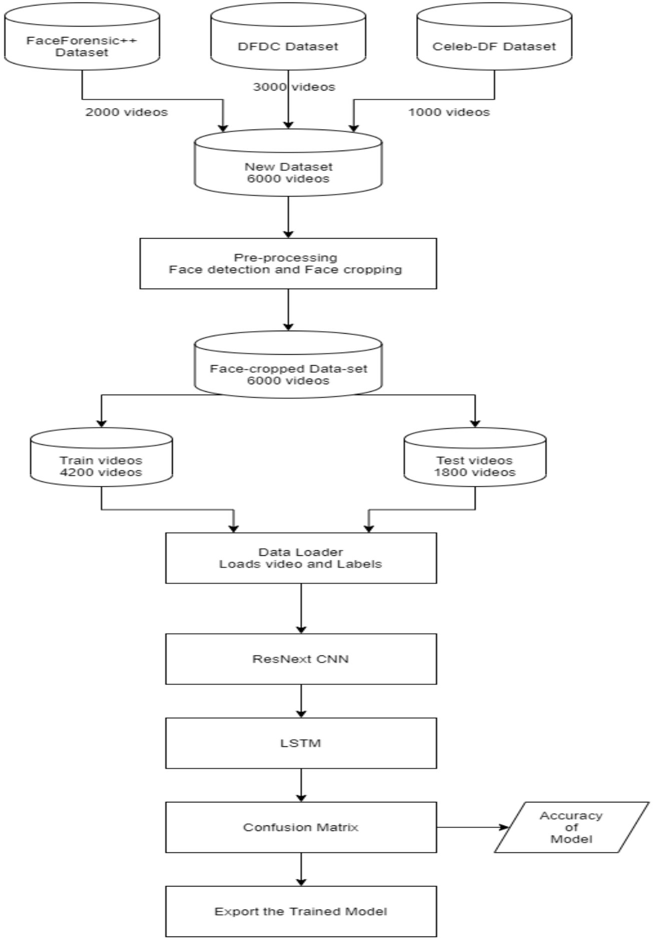
Sequential Layer

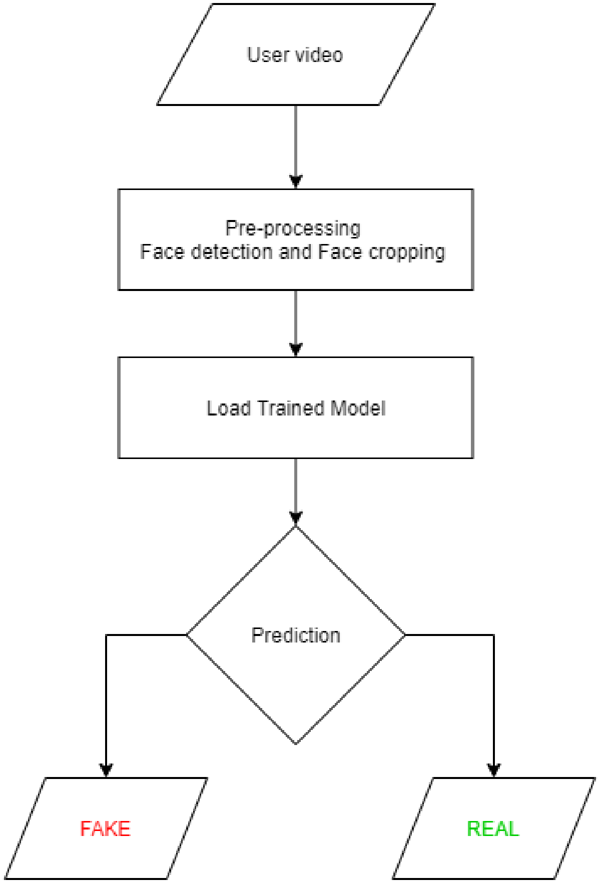
1 LSTM layer with 2048 shape input vector and 2048 latent features along with 0.4 chance of dropout and ReLU Activation function





Training Workflow





Prediction Workflow

Results

Model Name	Dataset	No of Videos	Sequence Length	Accuracy
model_90_acc_20_frames_FF_data	Face Forensic++	2000	20	90.95477387
model_95_acc_40_frames_FF_data			40	95.22613065
model_97_acc_60_frames_FF_data			60	97.48743719
model_97_acc_80_frames_FF_data			80	97.73366834
model_97_acc_100_frames_FF_data			100	97.76180905
model_84_acc_10_frames_final_data	Our Dataset	6000	10	84. 662519
model_87_acc_20_frames_final_data			20	87.79160186
model_89_acc_40_frames_final_data			40	89.3468118195956
model_91_acc_60_frames_final_data			60	91.5909797822706
model_92_acc_80_frames_final_data			80	92.4981855883877
model_93_acc_100_frames_final_data			100	92.10883877

CONCLUSION

REFERENCES

[1] X. Yang, Y. Li, and S. Lyu, "Exposing deep fakes using inconsistent head poses," ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing, 2019.

[2] C. Vaccari and A. Chadwick, "Deepfakes and disinformation: Exploring the impact of synthetic political video on deception, uncertainty, and trust in news," Social Media+ Society, vol. 6, pp. 2 056 305 120 903 408–2 056 305 120 903 408, 2020

[3] Sheng-Yu Wang, "CNN-generated images are surprisingly easy to spot...for now," Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020

[4] M. Masood, "Deepfakes Generation and Detection: State-of-the-art, open challenges, countermeasures, and way forward," Applied Intelligence, pp. 1–53, 2022.

Thank you