JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Survey on Development of Face Anti-Spoofing Detection Model through Deep Learning

Satish Kumar Nath
Lecturer- Computer Engineering
Board of Technical Education Rajasthan (BTER), Jodhpur

Abstract— **In recent years, face biometric security systems are rapidly increasing. Face-spoofing attacks, in which a spoofed face is presented to the biometric system in an attempt to be authenticated, are becoming an inevitable threat. Therefore, face-spoofing detection has become a critical requirement for any face recognition system to filter out fake faces. While face anti-spoofing techniques have received much attention to aim at identifying whether the captured face is genuine or fake, most face-spoofing detection techniques are biased towards a specific presentation attack type or presentation device; failing to robustly detects various spoofing scenarios.**

To mitigate this problem, we aim at developing a generalizable face-spoofing framework which able to accurately identify various spoofing attacks and devices. This innovative technology shows a lot of promise and change the way in which we can access sensitive information. But as promising as facial recognition is it does have flaws. User photos can easily be found on social networking sites and images can be spoofed. This is where the need of anti-spoofing comes into play. Face anti spoofing is the task of preventing false facial verification by using a photo, video/substitute for an authorized person's face.

Keywords* - *Anti-Spoofing, Deep Learning, Spoof Detection, Biometric Security, Facial Recognition, Liveness Detection, Presentation Attack, Convolutional Neural Networks (CNN), Feature Extraction, Multimodal Fusion, Imposter Detection, Supervised Learning, Unsupervised Learning

I. INTRODUCTION

Biometric systems such as face recognition, finger-print identification are extensively used for personal identification. It is more secured than any traditional methods like passcode-entry, ID card, or keys. Face recognition system is also more convenient than the traditional methods. However, Face recognition is often prone to presentation attacks. Presentation attack includes print and video/replay attacks. In print attack, the attacker utilizes the photo of a valid user presented in a digital device or printed in a paper. In video/replay attack, the attacker uses natural human movements of a valid user recorded in a video. Many different types of hardware and software methods have been developed to detect spoof faces.

Face anti-spoofing is crucial to prevent face recognition systems from a security breach. Previous deep learning approaches formulate face anti-spoofing as a binary classification problem. Many of them struggle to grasp adequate spoofing cues and generalize poorly. Face anti-spoofing techniques have received much attention and several anti-spoofing approaches have been introduced in retrospective studies [10, 19].

Traditional image-based approaches focus on image quality and characteristics and thus employ hand-craft features, such as LBP, SIFT, HOG, and SURF, with shallow classifiers to discriminate the live and fake faces [4, 7, 12]. These hand-crafted features are limited to specific spoofing patterns, scene conditions and spoofing devices, which limits their generalization [20]. Lately, deep methods based on Convolutional Neural Networks (CNNs) provide an alternative way to further push the effectiveness of anti-spoofing techniques via learning a discriminate representation in an end-to-end manner [19, 26]. While numerous machine learning models have been developed to discover artifacts in spoof images, the performance of spoofing models in practical settings is still far from perfect due to the following challenges. First, the available spoofing attack datasets are limited and bias to several environmental and capture settings as compared to other computer vision tasks such as image classification for which there exist large-scale labelled datasets, like ImageNet [8]

Majority of face spoofing attacks are known as presentation attacks. These attacks use 2D and 3D (static or dynamic) to fool facial recognition software. Static 2D presentation attacks rely on photographs, flat paper, or masks, while dynamic versions use screen video replays or several photographs in a sequence. Static 3D presentation attacks may use 3D prints, sculptures, or masks, while dynamic versions use sophisticated robots to reproduce expressions, complete with makeup.

II. *LITERATURE SURVEY*

Proposed real-time face anti-spoofing method based on stereo matching. Traditional CNN-based approaches for face anti-spoofing often lack robustness in varied scenes due to differing image qualities and environmental factors. To address this, the method introduces a lightweight stereo matching network, processing infrared face image pairs to generate a disparity map.[1] This map, providing depth information, is then fed into a classification network for determining face authenticity. Experimental results demonstrate significant performance enhancement compared to state-of-the-art methods, particularly excelling in real-time scenarios due to faster inference times and lower computational complexity.

A new approach to address the limitations of existing face anti-spoofing methods in combating advanced 3D attacks, particularly vivid masks is introduced [2]. The proposed Hypergraph Convolutional Neural Networks (HGCNN) leverages a computation-efficient and posture-invariant face representation using hypergraphs. By incorporating hypergraph convolution for feature extraction and depth information for 3D mask anti-spoofing, the method achieves state-of-the-art performance. Additionally, a comprehensive 3D face attack database, integrating colour, depth, and infrared light information, validates the effectiveness of the proposed paradigm. Experimental results demonstrate superior performance on both established and newly created 3D databases, establishing the method's efficacy in countering sophisticated spoofing attempts. Novel source data-free domain adaptive face anti-spoofing framework to enhance generalization capability while preserving data privacy is introduced [3]. By modelling the problem as learning with noisy labels, it optimizes the network in the target domain without using labelled source data. Dynamic images with background capture motion divergences between real and attack faces, while a self-ensemble filtering strategy reduces fluctuations caused by noisy labels. The approach demonstrates promising performance across public-domain face anti-spoofing databases.

The study addresses the poor generalization of conventional face anti-spoofing methods by employing multi-domain feature disentanglement. [4] It proposes a two-branch convolutional network to separate spoof-specific and domain-specific features from face images. A cross-adversarial training scheme minimizes correlation between these features, while a mixing augmentation approach enhances domain discrepancy, resulting in improved generalization across various public face anti-spoofing datasets. FARCNN introduced a face anti-spoofing method combining face detection and spoofing detection stages.[5] Leveraging an improved Faster R-CNN framework, it conducts three-way classification to discern real faces, fake faces, and backgrounds. Optimization strategies include roi-pooling feature fusion and Crystal Loss function integration. Additionally, an enhanced Retinex-based LBP addresses varying illumination conditions. The cascaded detectors achieve promising performance across benchmark databases, demonstrating effective generalization capabilities through cross-database experiments.

It highlights the necessity of face anti-spoofing due to the vulnerabilities of traditional RGB images to various attacks like photos, videos, and 3D masks.[6] Utilizing a binocular camera setup combining RGB and NIR, a novel RGB + NIR face database is created. Leveraging NIR information, which is more resistant to electronic device spoofing, feature vectors are extracted for binary classification, yielding excellent results. Real-life application demonstrates significant progress, affirming the effectiveness of the proposed scheme. Deep learning model is introduced for domain-generalized face anti-spoofing (FAS), aiming to discern spoof attacks from authentic ones across different image domains.[7] The proposed network disentangles facial liveness representation from irrelevant features like facial content and image domain, ensuring domain-invariant properties. Experimental validation on five benchmark datasets demonstrates the model's efficacy in identifying novel spoof attacks in unseen domains, outperforming state-of-the-art approaches and highlighting its potential for broader FAS applications.

The study proposes an adversarial learning framework to estimate spoof-related patterns for face anti-spoofing, focusing on subtle image patterns termed "spoof trace."[8] Through a two-step disentanglement process, spoof traces are separated from live counterparts, facilitating adversarial learning and data augmentation. Frequency-based image decomposition enhances low-level vision cues. The approach achieves superior spoof detection across various scenarios, providing visually convincing spoof trace estimations. Upon publication, the source code and pre-trained models will be publicly available. Face anti-spoofing is essential for ensuring the security of face verification and recognition systems, but existing CNN models often struggle to generalize across different datasets, impacting their effectiveness against unseen attacks. [9] Through experiments on challenging datasets like CASIA and Replay-Attack, we reveal the limitations of CNNs in adapting from one dataset to another. By visualizing CNN attention, we identify scene-dependent features as a hindrance to generalization and propose a solution based on scene-independent feature representation.

The growing use of face recognition systems brings convenience but also vulnerability to spoofing attacks. This study reviews existing anti-spoofing methods, compiling research from various authors found through online sources. [10] It discusses different approaches to face spoof detection, types of spoof attacks, and categorizes anti-spoofing methods. Results are presented in tables, detailing publicly available face anti-spoof databases and comparing the performance of various approaches, offering insights into the landscape of face anti-spoofing research. The widespread use of face recognition in various applications raises concerns about spoofing attacks.[11] To address this issue, we propose an anti-spoofing system based on local texture features. We employ Quaternionic Local Ranking Binary Pattern (QLRBP) to extract local features from input images. These features are then evaluated using K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) classifiers. Our experiments on publicly available datasets demonstrate that our system achieves high accuracy, reaching up to 95.20% with KNN and 97.36% with SVM. These results highlight the effectiveness of QLRBP features for face anti-spoofing applications. Face anti-spoofing remains challenging with monocular images due to their complex appearance, necessitating large amounts of training data.[12] To address this, we propose a novel method based on distributed learning, emphasizing privacy preservation and enhanced data utilization. Our approach, Distributed Hypergraph Laplacian (DHL), leverages manifold learning to capture semantic relationships among training data in a distributed manner. By representing images via the eigen decomposition of the manifold matrix, original data is safeguarded. Additionally, hypergraph Laplacian is integrated to enhance robustness. Evaluation on MSSPOOF and CASIA-SURF datasets demonstrates the effectiveness of DHL in improving face anti-spoofing performance.

An efficient anti-spoofing method is introduced for face recognition systems, leveraging pair wise discrete cosine transform coefficients and logistic regression.[13] Experimental results demonstrate its superiority over the widely used local binary patterns approach, offering enhanced accuracy in distinguishing between genuine and fake faces presented to cameras. The challenge of cross-dataset generalization in face anti-spoofing is addressed by treating it as a domain generalization problem.[14] Introducing a meta-learning approach with regularization and convex optimization, the method leverages domain knowledge to enhance feature space regularization, employs a linear classifier, and applies convex optimization to mitigate computational challenges. Experimental results across three public datasets demonstrate state-of-the-art performance.

Challenges of limited diversity in existing face anti-spoofing datasets are addressed in hindering model generalization.[15] Introducing the Dual Spoof Disentanglement Generation (DSDG) framework, the method leverages Variational Autoencoder (VAE) disentanglement to learn joint distributions of identity and spoofing patterns, generating diverse paired live and spoofing images. To handle distorted images, a Depth Uncertainty Module (DUM) is introduced, enhancing depth supervision. Evaluation across five benchmarks demonstrates state-of-the-art performance in both intra- and inter-test scenarios A novel face anti-spoofing model is introduced by comprising two streams to integrate high and low-frequency information from facial images, enhancing generalization capability across datasets.[16] By employing high-pass and low-pass filters, the model extracts corresponding components and processes them through sub-networks with cross-frequency spatial attention (CFSA). After incorporating self-channel attention, the outputs are fused for classification. Experimental results demonstrate significant improvement in cross-database generalization for face spoofing detection.

Two streamlined approaches for face anti-spoofing are introduced, focusing on eye movement detection and CNN-based liveness detection through local feature extraction.[17] Experiments evaluate the proposed methods against previous works using Half Total Error Rate (HTER) across three datasets: NUAA imposter dataset, Replay Attack, and a newly introduced OWN replay dataset. TransFAS, a novel system is introduced for Face Anti-Spoofing (FAS) based on Video Vision Transformer (VVT), addressing limitations of traditional CNNs in extracting relative object placement. [18] TransFAS operates by extracting tokens from multiple frames, embedding them with positional information to preserve spatial relationships, and passing them through a Transformer Encoder for prediction. Trained on Replay-Attack and 3DMAD datasets, TransFAS outperforms existing models in spoof detection.

Face recognition system is derived with anti-spoofing features to address security concerns posed by spoofing attacks.[19] Leveraging the ResNet50 neural network architecture for face recognition, the system integrates eye blink detection for photo attacks and reflection of light detection for video attacks. A hardware prototype is developed to implement these functions. This approach aims to enhance the security of facial recognition systems by detecting and preventing spoofing attempts, thereby safeguarding critical data and facilities from unauthorized access. The significance of face anti-spoofing is addressed, particularly in countering video attacks, an area that has received less attention compared to photo attacks[20]. Instead of analyzing individual images, the study focuses on extracting spatiotemporal features from continuous video frames using a 3D convolutional neural network (CNN). Experimental results demonstrate superior performance on two widely-used face anti-spoofing databases, Replay-Attack and CASIA, with significantly lower Half Total Error Rates (HTER) compared to existing approaches, highlighting the effectiveness of the proposed method in detecting video spoofing attempts.

A security classification framework is introduced, that integrates face recognition with anti-spoofing capabilities to address access control system vulnerabilities, including mask-wearing recognition challenges [21]. Evaluation on CASIA-FASD benchmarks yields promising results: Half Total Error Rate (HTER) at 9.7% and Equal Error Rate (EER) at 5.5%, showcasing its high anti-spoofing efficacy for real-time mask detection on embedded systems. An effective face anti-spoofing method is proposed that leveraging optical flow vectors to detect spoofing attacks from both photos and videos displayed on electronic screens.[22] By analyzing displacement differences between successive frames, the method demonstrates promising results on the REPLAY-ATTACK database, effectively distinguishing between real faces and spoofing attempts. A deep neural network is introduced approach for face anti-spoofing and liveness detection to address the vulnerability of face recognition systems to various spoofing attacks[23]. Experimental results confirm the method's robustness against print, cut, and replay attacks, enhancing the security of face recognition systems. Auto-FAS is introduced. [24] It is a novel approach for face anti-spoofing (FAS) optimized for mobile devices. Leveraging neural architecture search (NAS), Auto-FAS discovers lightweight networks tailored for real-time FAS on portable devices. A specialized search space limits model size, while pixel-wise binary supervision enhances performance. Experimental results on three benchmark datasets underscore the efficacy and efficiency of Auto-FAS, highlighting its suitability for mobile FAS applications. Challenge of detecting realistic 3D face presentation attacks ARE INTRODUCED, proposing a novel anti-spoofing method, MC_FBC, based on fine-grained classification.[25] Leveraging factorized bilinear coding across multiple color channels, it extracts and fuses discriminative information from RGB and

YCbCr spaces. Extensive experiments demonstrate state-of-the-art performance on diverse datasets, including a newly collected wax figure face database (WFFD).

III A COMPARISON IN TABULAR FORM

This table provides a concise comparison of the methodologies and contributions of each paper in the context of Anti-Spoofing Detection Models through Deep Learning.

SN	Paper Title and Approach	Key Methodologies and Contributions
1	An Effective Face Anti-Spoofing Method via Stereo Matching	Utilizes stereo matching for disparity map generation followed by classification using CNN.
2	Exploring Hypergraph Representation On Face Anti-Spoofing	Introduces Hypergraph Convolutional Neural Networks for 3D face anti-spoofing.
3	Combining Dynamic Image and Prediction Ensemble for Cross-Domain Face Anti-Spoofing	Proposes a source data-free domain adaptive framework using dynamic images and filtering strategies.
4	Generalized Face Anti-Spoofing via Cross-Adversarial Disentanglement	Uses a two-branch convolutional network with cross-adversarial training for spoof-specific feature disentanglement.
5	A Cascade Face Spoofing Detector Based on Face Anti-Spoofing R-CNN & Improved Retinex LBP	Introduces FARCNN and improved Retinex LBP for a cascaded face spoofing detector.
6	Face Anti-Spoofing Based on NIR Photos	Utilizes NIR information for face anti-spoofing and achieves excellent results.
7	Learning Facial Liveness Representation for Domain Generalized Face Anti-Spoofing	Proposes a deep learning model for domain-generalized face anti-spoofing using disentangled liveness representation.
8	Spoof Trace Disentanglement for Generic Face Anti-Spoofing	Presents an adversarial learning framework for estimating spoof-related patterns.
9	Scene-Independent Feature Representation for Face Anti-Spoofing	Introduces a solution based on scene-independent features representation.
10	Quaternionic Local Ranking Binary Pattern Features for Face Anti-Spoofing	Proposes a face anti-spoofing system based on Quaternionic Local Ranking Binary Pattern features.
11	Distributed Hypergraph Laplacian for Face Anti-Spoofing with Monocular Images	Introduces DHL for learning semantic relationships among training data in a distributed way.
12	Face Anti-Spoofing Based on Image Block Difference and Logistic Regression Analysis	Utilizes logistic regression with image block difference for face anti-spoofing.
13	Meta Face Anti-Spoofing with Regularization and Convex Optimization	Addresses domain generalization problem using meta-learning with regularization and convex optimization.
14	Dual Spoof Disentanglement Generation for Face Anti-Spoofing with Depth Uncertainty Learning	Proposes DSDG framework for face anti-spoofing via generation and depth uncertainty learning.
15	Fusion of High & Low Freq Features for adv Generalization Capability in Face Anti-Spoofing	Introduces a method to fuse high and low-frequency features for improved generalization capability.
16	Eyes Movement and CNN-based Liveness Detection for Face Anti-Spoofing	Proposes two approaches for face anti-spoofing based on eyes movement and CNN-based liveness detection.
17	Transformer-based Network for Face Anti-Spoofing using Token Guided Inspection	Introduces TransFAS based on Video Vision Transformer for face anti-spoofing.

IV CONCLUSION

In conclusion, this survey highlights the remarkable progress in face anti-spoofing detection achieved through deep learning techniques. By examining various methodologies and advancements, we observe the evolution from traditional feature-based approaches to sophisticated deep neural networks. Deep learning models, with their ability to extract intricate patterns and representations, have significantly enhanced the accuracy and robustness of face anti-spoofing systems. However, challenges such as domain adaptation and generalization persist, urging further research. As the field continues to mature, ongoing innovations promise to fortify face recognition systems against increasingly sophisticated spoofing attacks, advancing security and trust in biometric authentication technologies.

REFERENCES

[1] Z. Li, J. Yuan, B. Jia, Y. He and L. Xie, "An Effective Face Anti-Spoofing Method via Stereo Matching," in IEEE Signal Processing Letters, vol. 28, pp. 847-851, 2021.

[2] G. Te, W. Hu and Z. Guo, "Exploring Hypergraph Representation On Face Anti-Spoofing Beyond 2d Attacks," 2020 IEEE International Conference on Multimedia and Expo (ICME), London, UK, 2020, pp. 1-6.

[3] L. Lv et al., "Combining Dynamic Image and Prediction Ensemble for Cross-Domain Face Anti-Spoofing," ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Toronto, ON, Canada, 2021, pp. 2550-2554.

[4] H. Huang et al., "Generalized Face Anti-Spoofing via Cross-Adversarial Disentanglement with Mixing Augmentation," ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Singapore, Singapore, 2022, pp. 2939-2943.

[5] H. Chen, Y. Chen, X. Tian and R. Jiang, "A Cascade Face Spoofing Detector Based on Face Anti-Spoofing R-CNN and Improved Retinex LBP," in IEEE Access, vol. 7, pp. 170116-170133, 2019.

[6] Z. Shi, H. Zhang, Z. Gao and L. Huang, "Face Anti-Spoofing Based on NIR Photos," 2019 IEEE 13th International Conference on Anti-counterfeiting, Security, and Identification (ASID), Xiamen, China, 2019, pp. 31-35.

[7] Z. -C. Chen, L. -H. Tsao, C. -L. Fu, S. -F. Chen and Y. -C. F. Wang, "Learning Facial Liveness Representation for Domain Generalized Face Anti-Spoofing," 2022 IEEE International Conference on Multimedia and Expo (ICME), Taipei, Taiwan, 2022, pp. 1-6.
J. D. Musa, "A theory of software reliability and its application," IEEE Trans. Software Eng., vol. SE-1, pp. 312-327, Sept. 1975.

[8] Face anti-spoofing (FAS) aims at distinguishing face spoof attacks from the authentic ones, which is typically approached by learning proper models for performing the associated

[9] Y. Liu and X. Liu, "Spoof Trace Disentanglement for Generic Face Anti-Spoofing," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 3, pp. 3813-3830, 1 March 2023.

[10] W. -S. Qi, H. -M. Ding, Y. -B. Wang and Z. -F. Xie, "Scene-Independent Feature Representation for Face Anti-Spoofing," 2018 International Conference on Audio, Language and Image Processing (ICALIP), Shanghai, China, 2018, pp. 123-127.

[11] P. Anthony, B. Ay and G. Aydin, "A Review of Face Anti-spoofing Methods for Face Recognition Systems," 2021 International Conference on INnovations in Intelligent SysTems and Applications (INISTA), Kocaeli, Turkey, 2021, pp. 1-9.

[12] A. Cornelia, I. Setyawan and G. Dewantoro, "Face anti-spoofing method based on quaternionic local ranking binary pattern features," 2018 International Conference on Signals and Systems (ICSigSys), Bali, Indonesia, 2018, pp. 92-97.

[13] X. Lin, C. Hong, X. Liang and L. Liu, "Distributed Hypergraph Laplacian for Face Anti -spoofing with Monocular Images," 2022 International Conference on High Performance Big Data and Intelligent Systems (HDIS), Tianjin, China, 2022, pp. 131-135.

[14] H. Kang, "Face anti-spoofing based on image block difference and logistic regression analysis," 2015 IEEE 5th International Conference on Consumer Electronics - Berlin (ICCE-Berlin), Berlin, Germany, 2015, pp. 493-495.

[15] Y. Zhang and P. Fang, "Meta Face Anti-spoofing with Regularization and Convex Optimization," 2020 IEEE 14th International Conference on Anti-counterfeiting, Security, and Identification (ASID), Xiamen, China, 2020, pp. 58-62.

[16] H. Wu, D. Zeng, Y. Hu, H. Shi and T. Mei, "Dual Spoof Disentanglement Generation for Face Anti-Spoofing With Depth Uncertainty Learning," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 32, no. 7, pp. 4626-4638, July 2022.

[17] B. Chen, W. Yang and S. Wang, "Face Anti-Spoofing by Fusing High and Low Frequency Features for Advanced Generalization Capability," 2020 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), Shenzhen, China, 2020, pp. 199-204.

[18] P. P. P. Linn and E. C. Htoon, "Face Anti-spoofing using Eyes Movement and CNN-based Liveness Detection," 2019 International Conference on Advanced Information Technologies (ICAIT), Yangon, Myanmar, 2019, pp. 149-154.

[19] D. Chaudhry, H. Goel and B. Verma, "TransFAS: Transformer-based network for Face Anti-Spoofing using Token Guided Inspection," 2023 IEEE 8th International Conference for Convergence in Technology (I2CT), Lonavla, India, 2023, pp. 1-7.

[20] S. Savanth, K. G. R. Manish, P. Narayan, M. L. Nikhil and V. G. Gokul, "Face Recognition System with 2D Anti-Spoofing," 2022 IEEE World Conference on Applied Intelligence and Computing (AIC), Sonbhadra, India, 2022, pp. 226-230.

[21] J. Gan, S. Li, Y. Zhai and C. Liu, "3D Convolutional Neural Network Based on Face Anti-spoofing," 2017 2nd International Conference on Multimedia and Image Processing (ICMIP), Wuhan, China, 2017, pp. 1-5.

[22] X. Wu, D. Zhang and X. Liu, "Primary Study on the Face-recognition Framework with anti-spoofing function," 2022 4th International Conference on Data Intelligence and Security (ICDIS), Shenzhen, China, 2022, pp. 474-477.

[23] W. Yin, Y. Ming and L. Tian, "A face anti-spoofing method based on optical flow field," 2016 IEEE 13th International Conference on Signal Processing (ICSP), Chengdu, China, 2016, pp. 1333-1337.

[24] H. -Y. S. Lin and Y. -W. Su, "Convolutional Neural Networks for Face Anti- Spoofing and Liveness Detection," 2019 6th International Conference on Systems and Informatics (ICSAI), Shanghai, China, 2019, pp. 1233-1237.

[25] Z. Yu et al., "Auto-Fas: Searching Lightweight Networks for Face Anti-Spoofing," ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 2020, pp. 996-1000.

[26] S. Jia, X. Li, C. Hu, G. Guo and Z. Xu, "3D Face Anti-Spoofing With Factorized Bilinear Coding," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 31, no. 10, pp. 4031-4045, Oct. 2021.

Satish Kumar Nath is Lecturer – Computer Engineering in Board of Technical Education Rajasthan (BTER), Jodhpur

Name: Satish Kumar Nath

Mobile Number: +91-9829632667

Mail id: satishkumar.nath@gmail.com

Communication Details:

Board of Technical Education Rajasthan (BTER), Jodhpur

W-6, Residency Road, Jodhpur, Rajasthan