2025 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI) | 979-8-3315-2169-1/25/$31.00 ©2025 IEEE | DOI: 10.1109/IATMSI64286.2025.10985684

Developing a Face Aging Model Using Face Synthesis Techniques

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***Abstract*—Regarding the realm of advancing technology, the subsequent development of face aging applications has garnered substantial interest. This research examines face synthesis techniques, with specific emphasis for the various practical usage of computational adversarial networks (GANs). The key objective of our project is to upgrade both the discriminator and the generator parts of GANs to generate more realistic, age-progressed face images. The project assimilates Python programming, convolutional neural networks (CNNs), and several other machine learning and image processing proceeds, advancing in qualitative data from Kaggle. The goal of our project is to advancement of face- aging technology over the use of this multifaceted method, with the possible uses in amusement, forensic science, and technological process.**

***Index Terms*—Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), Generator, Discriminator**

I. Introduction

To try to smooth the puzzles of time's transit engraved on human figures, the marriage of artificial intelligence and photographic synthesis has appeared as a transformative force. This aging phenomenon of face, has basically natural, enchanted researchers and expounders across disciplines, from forensic science to entertainment, outstanding its profound implications and diverse applications [1]. The face aging field of face synthesis has adapted an experienced a prototype change with the development of deep learning approaches, primarily Generative Adversarial Networks (GANs), which have generated in previously unattainable levels of naturalism and consistency in age progression cumulation [2].

Previously, age cycle methods mostly depended on human adaptations or fundamental programming that couldn't adequately behold the exclusiveness of facial aging. However, the introduction of GANs by Goodfellow in 2014 signalled a revolution in the field of generating various models. The primary concept behind how GANs function is that ,how a discriminator network tries to differentiate between the actual and artificial samples, while a generator network make efforts achieving aim to create realistic data samples [3]. Both the networks grind their skills through an iterative adversarial procedure, giving results in the creation of lifelike images. After merging computer vision, machine learning, and

image processing, the main purpose of GANs for addressing aging synthesis tells how to transform the several fields and fundamentally transform the understanding of aging dynamics.

This article addresses unsolved issues by upgrading the generation procedure as a discriminator's performance and providing a thorough overview of the most recent developments in face aging synthesis using GANs. In this we researched the underneath concepts behind GANs and how they are used for generating realistic facial images. We then examined a wide range of methods which focused at negotiating with certain situations which are associated with face aging, such as time progression reliability, authenticity, and personality preservation [4].

Further , we have explained how evaluation demands and standard datasets portray a vital role while assessing the effectiveness of face aging models and clarify the subtle aspects of sensation stature, age advancement commitment, and identity preservation. We have also looked at the revolutionary potential of GAN-based face aging synthesis in a variety of operations, from digital amusement platforms to fingerprint verification systems, furthermore in the technical components.

However regardless of the clear future, there are the meaningful ethical questions and society implications to ponder. The putting together of intentionally aged images opens up questions about permission, privacy, and the prospective abuse of synthetic data. Therefore , we enhance the value of responsible invention and ethical governance in exploiting the energize of GANs for face aging synthesis. [5].

II. LITERATURE REVIEW

Li and Lee (2023) proposed GFAM, a gender-preserving face aging model, addressing age imbalance in datasets. Their approach ensures realistic aging effects while maintaining gender-specific facial characteristics, enhancing dataset diversity and training efficiency [6]. Liu et al. (2020) employed data augmentation and lightweight CNNs for face age estimation, achieving efficient performance on limited hardware. Their model's simplicity and effectiveness make it suitable for real-time applications [7]. Wan and Lee (2019) introduced a joint training model for face sketch synthesis, enabling better collaboration between photo-to-sketch and sketch-to-photo tasks. This bidirectional approach improves synthesis accuracy, especially in law enforcement applications [8]. Rathore et al. (2024) presented a smart ecosystem for skin cancer detection, leveraging advanced image processing and machine learning. Their system enhances diagnostic accuracy, integrating seamlessly with healthcare applications [9]. Sun et al. (2005) proposed a novel method using EHMM for aging face recognition. Despite being an earlier work, their approach laid the groundwork for integrating probabilistic models into face aging tasks [10]. Boussaad and Boucetta (2021) explored the impact of aging on face recognition algorithms, identifying variations in accuracy across age groups and gaps [11]. This study underlined the challenges posed by aging factors in maintaining reliable face recognition, emphasizing the necessity for adaptive algorithmic strategies. Suo et al. (2012) introduced a Concatenational Graph Evolution Aging Model to address age progression in face recognition [12]. Their work provided a novel approach for aging simulation, significantly contributing to the development of age-invariant recognition systems. Shrivastava and Rathore (2024) analyzed a single-server Markovian queuing model with unique considerations like working vacations and customer reneging [13]. This research added depth to operational modeling in queue systems, offering insights applicable to intelligent systems like customer-facing AI. Osman and Viriri (2018) conducted a comprehensive survey on face verification across age progression, summarizing state-of-the-art methodologies [14]. Their work highlighted key challenges and advances in creating age-invariant verification systems. Rathore (2023) examined AI's transformative role in recruitment, detailing its efficacy in automating and enhancing selection processes [15]. This study illuminated AI's potential to streamline HR practices. Zhao et al. (2022) proposed advanced techniques towards achieving age-invariant face recognition [16]. Their study demonstrated improved accuracy by mitigating the effects of age-related variances on facial features. Fu, Guo, and Huang (2010) provided a survey on age synthesis and estimation, summarizing various facial analysis techniques [17]. This foundational work guided subsequent research in age-related facial analysis. Rathore et al. (2024) explored consumer sentiment analysis, focusing on applications in intelligent systems [18]. Their findings demonstrated the utility of sentiment analysis in understanding consumer behavior. Antipov, Baccouche, and Dugelay (2017) utilized conditional generative adversarial networks for face aging [19]. Their work advanced generative modeling, enabling realistic aging simulations. Wu, Du, and Hu (2021) developed a Parallel Multi-Path Age Distinguish Network for cross-age face recognition [20]. Their model achieved remarkable accuracy, addressing the complexities of cross-age facial comparisons. Su, Wang, and Bao (2015) employed Bayesian inference for age-variation face recognition [21]. Their probabilistic approach improved recognition reliability across diverse age groups. Kaushik (2024) discussed dynamic data scaling techniques for streaming machine learning [22]. This study provided scalable solutions for real-time data processing challenges in AI applications. Genovese, Piuri, and Scotti (2019) investigated explainable face aging using generative adversarial networks [23]. Their research bridged the gap between interpretability and generative face modeling. Rathore et al. (2024) integrated fog and edge computing for intelligent transportation systems [24]. Their work emphasized the role of distributed computing in enhancing navigation systems. Somada, Ohyama, and Wakabayashi (2017) proposed segmentation verification for age-invariant person identification [25]. This method improved the robustness of identification systems across varying age groups. Wang et al. (2023) addressed cross-age face recognition challenges for digital archives [26]. Their study presented practical solutions for preserving recognition accuracy in archival systems.

III. METHODOLOGY

In recent, face ageing application has gained interests because of its wide range applications in fields of entertainment, forensics etc.. However, the obstacle lie in the generation of the aged faces from the young face inputs. Therefore, Generative Adversarial Networks, a face synthesis techniques provide a promising solution in this direction by producing a high quality images. It consists of 2 neural network which helps in one aims at generating the realistic images whereas other differentiate between the real and the fake images.

A methodological approach to building face aging applications using face synthesis is presented in this paper having main and specific focus on improving the performance of the discriminator and generator components of the adversarial network. The primary objective was to develop a robust and efficient system which is capable of generating realistic aged faces images from young face inputs [27]. This is achieved through machine learning, Python programming language, Convolutional Neural Networks (CNNs), and image processing techniques.

The qualitative data that we utilized was collected from Kaggle, a widely-used platform for sharing datasets and conducting data-driven research. The dataset collected had been pre-processed so as to ensure the consistency and quality in the inputted data. Facial alignment to normalize face orientations, resize images to a standard resolution had been performed and then pixel values are normalized to a common scale. Moreover, we had employed data augmentation techniques I.e. rotation, flipping, and scaling so as to increase variability of the dataset and also improving the robustness of the trained model.

An iterative training process had been adopted for the GAN, where both the generator and discriminator networks were trained simultaneously. During training, appropriate loss functions are defined including adversarial loss, feature perceptual loss, and matching loss for guiding the optimization of the discriminator and generator. Transfer learning techniques might also be utilized, initializing the GAN with pre-trained models to expedite convergence. The training processes were carried out using TensorFlow which facilitates efficient computation and scalability.

For evaluating the performance of the trained GAN, quantitative and qualitative metrics were done. Quantitatively, the generator and discriminator both are analysed on the basis of loss weights which carry out the training process. Different metrics are included such as generative adversarial loss, feature matching loss, and age classification accuracy to assess the quality and variety of the generated aged faces. Qualitatively, visual inspections and human evaluation studies were conducted so as to compare the generated images with ground truth aged faces from the dataset collected from Kaggle, ensuring the visual realism and perceptual quality of the result.

The proposed methodology was implemented using Python programming language, through TensorFlow for model training and evaluation. Extensive experimentation was conducted for exploring several hyperparameters, network architectures, and training strategies [28]. For feature extraction and representation learning, CNNs were employed, while machine learning techniques were utilized for data analysis and model optimization.

Python programming which is a versatile programming language, is used to carry out the implementation process because of its readability and rich libraries. CNN plays a vital role the Identity preserved CGANs framework for both the generator and the discriminator. CNNs abilities helps to identify and extract common image patterns vital for generating the images along with identity preservation. Image processing techniques help in pre-processing the training data and face detection, alignment etc. are done to normalize the input images. An open-source ML platform i.e. TensorFlow is used to train and deploy the network because of its robustness in handling the large datasets.

The output of the experiments demonstrated the potencial of the proposed methodology in improving the performance of the discriminator and generator in the face aging applications. We have presented the quantitative metrics and qualitative assessments, showing the quality and realism of the generated aged faces. We have compared the performance and discussed the implications of our findings of our approach with existing techniques, highlighting the advantages or limitations.

An important factor of building face aging applications using face synthesis was the selection of an appropriate GAN architecture and hence evaluated several architectures including IPCGAN, DCGAN, StyleGAN, and Pro-GAN, considering the factors such as computational efficiency and image quality. Based on the evaluation, we chose a GAN architecture that had strike a balance between these factors and was well-suited for the tasks of face synthesis [29]. The generator and discriminator networks were designed using CNN architectures which is optimized for image generation and discrimination. TensorFlow was also employed because of its efficiency and flexibility in implementing deep learning models.

In the paper, we have shown a methodological approach for building face aging applications using the approach GANs architecture such as IPCGAN and CGAN which produce the aged face images from the young inputs provided and also having a special focus on improving the performance of the discriminator and generator using GANs.

Network Architecture In this paper, we have implemented the IP-CGAN i.e. Identity Preserved Conditional GAN which is used because of its dual objective. Firstly, it generates realistic aged images from the young face inputs and also preserve the identity of the inputted image.

In IP-GAN generator comprises of several convolutional layers, un-sampling layers and residual blocks. The layers are designed to transform the input face images into the aged face images and also preserving the identity features. Figure 1 shows the network architecture of the model. It leverages various activation functions and regularization techniques in order to make smooth and natural age progression. On the other hand, discriminator network in IP-CGAN differentiate between real and fake images while at the same time preserve the identity information. Like generator, it also employs a series of convolutional layer, down sampling layers, and fully connected layers in order to effectively differentiate between real and synthesized images.

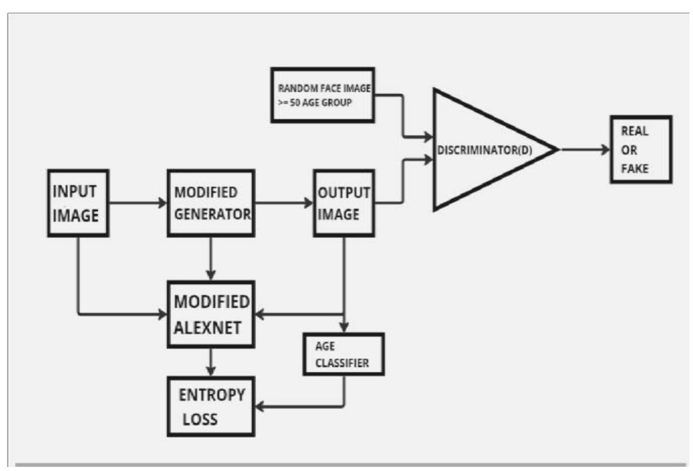

Fig. 1. Network Architecture

The research focused on contributing to advancing the fields of face aging technology, offering a robust and efficient solution so as to generate a realistic aged faces from young face inputs. We anticipated that our proposed methodology would inspire further research and development in the following area and opening new avenues for applications in various sectors.

IV. IMPLEMENTATION

Experimental Setup: For the paper, we have explored face aging effects using Identity-Preserved Conditional Generative Adversarial Networks as presented in paper[10]. We have setup the experimental environment with the different libraries and dependencies. TensorFlow-gpu of version 1.4.1 is utilized for the GPU resources. SciPy, OpenCV-python and NumPy are the core dependencies used for addressing the scientific computing and image processing needs. CUDA toolkit is also installed in order to ensure the compatibility and optimal performance with Tensor Flow gpu.

Dataset: In this paper we have chosen Cross Age Celebrity Dataset from Kaggle for the purpose of training and evaluation. The dataset holds more than 1 lakh images of approximately 2000 celebrities with age between 15 to 65. All the images in the dataset have large variation in pose, illumination, expressions and their styles. The dataset is partitioned into two parts: training and test data where training data is categorized into groups according to ages.

Model Evaluation: We have implemented the IPCGAN i.e. Identity Preserved Conditional Generative Adversarial Network approach in our paper. In the paper, we have first compared the different GANs methods with our method which are all build on conditional GANs and are quite similar to our method. We have used TensorFlow- GPU, scipy and numpy libraries for the implementation of our method. We started training the data from the scratch where we first downloaded the pre-trained model, including AlexNet and an age classification model where age classifier is finetuned on celebrity training dataset with 200000 steps and the whole training process complete in about 5 lakh steps. Additionally, we employed specific hyperparameters such as age loss weight, feature loss weight to balance the identity preservation and the aging effect. We have chosen conv5 feature layer for the feature extraction so as to optimize face ageing translation.

Loss Function: We have utilized the loss functions for the training of generator and discriminator of the IP-CGANs. The adversarial loss function encourages the generator for producing more realistic images in order to fool the discriminator and the feature matching loss ensures that the images generated matched the real images in order to preserve the identity of the different age groups. These loss functions are important to maintain the balance between the uniqueness of the identity characteristics and age progression and thereby increasing the performance of the network.

Improvement: To enhance the performance of the generator and the discriminator within IP-CGANs, AlexNet, a pre trained model and age classification models are used for the purpose of quick convergence and better generalization through the transfer learning. Hyperparameter tuning such as adversarial loss and the feature matching loss helps ensures a balance between the networks. Feature extraction layer such as conv5 ensures the identity preservation along with the introduction of the age-specific features.

V. RESULT AND DISCUSSION

In our paper, we have compared the effectiveness of the Identity Preserved Conditional Generative Adversarial Networks with many other approaches.

Fig. 2. Some results of IPCGANs

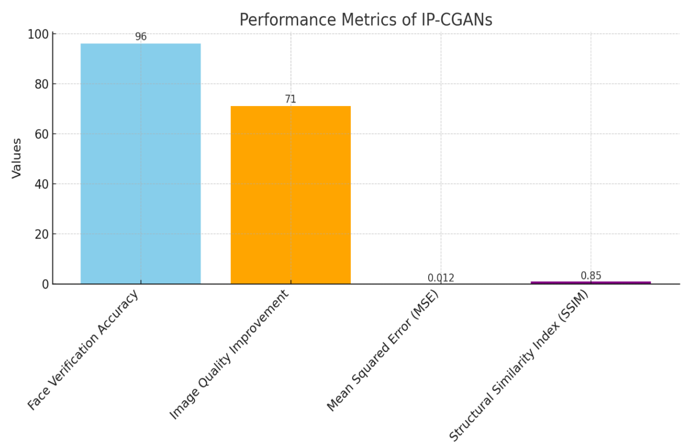

Fig. 3. Performance Metrics of IP-CGNs

that the mean squared error of the input and the generated image is also reduced with the IP-CGANs method. The mean square error score of approx. 0.012 and the structural similarity index of 0.85 shows high fidelity and similarity with the target. This shows the ability of the model in preserving the integrity of the image identity throughout the ageing process. Quantitative assessment also shows that proposed approach has demonstrated higher accuracy in comparison with the baseline.

Qualitative analysis shows that while doing the visual examination of the result, close resemblance of the generated

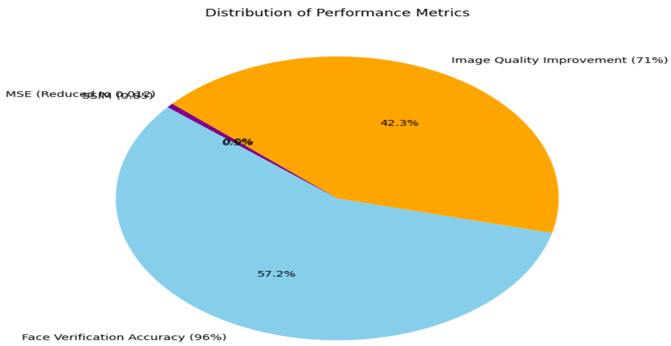

Fig. 4. Distribution Performance Metrics

aged faces found with the targeted aged faces which shows the preservation of the identity of the input face.

IP-CGANs has various applications in multiple domains such as digital entertainment, security, and helping find missing persons. This identity-preserved aging model holds promise for improving the precision of age-progressed images in these highly sensitive domains.

It is also important to acknowledge the constraints in our study. First of all our results depends upon the quality and diversity of the training dataset utilized. Moreover, the computational resources, necessary for the training and inference, might bring various restrictions and demerits to the feasibility of our approach when used with real time scenarios.

VI. CONCLUSION

This paper has proposed improvement to both the network components of the generative adversarial network i.e. generator and discriminator. Through the current development in this field, a comprehensive overview has been offered in the face ageing using GANs approach. IPCGAN, a GANs methodology is used in the paper with its dual objective of both enhancing the performance and the fidelity of the generated aged images from the young inputs along with the identity preservation makes it a valuable tool for the accurate representation of the implemented approach of age progression. Further, to achieve more promising outputs and to enhance the realism of the results, main focus would be on the refinement of the model's architecture and methodologies.

Moreover, the paper stresses on the necessity of ethical scrutiny which are responsible for the development of the face synthesis technology by emphasising on the importance of potential biases and moral implications investigation. Altogether, the approach presented in the paper pave a way for continuing progress in the face synthesis application across various fields such as healthcare, forensics, entertainment industry etc.

REFERENCES

[1] X. Liu, Y. Zou, C. Xie, H. Kuang, and X. Ma, "Bidirectional Face Aging Synthesis Based on Improved Deep Convolutional Generative Adversarial Networks," *Information*, vol. 10, no. 2. MDPI AG, p. 69, Feb. 18, 2019.

[2] K.ELKarazle, V. Raman, and P. Then, "Facial Age Estimation Using Machine Learning Techniques: An Overview," *Big Data and Cognitive Computing*, vol. 6, no. 4. MDPI AG, p. 128, Oct. 26, 2022.

[3] S. Pathania et al., "An Efficient Electrical-Thermal Co-Design Methodology for Analysis of High-Speed PCB Interconnects," 2023 *IEEE MTT-S International Conference on Numerical Electromagnetic and Multiphysics Modeling and Optimization (NEMO)*, Winnipeg, MB, Canada, 2023, pp. 154-157.

[4] C. Li, Y. Li, Z. Weng, X. Lei, and G. Yang, "Face Aging with Feature-Guide Conditional Generative Adversarial Network," *Electronic*s, vol. 12, no. 9. MDPI AG, p. 2095, May 04, 2023.

[5] Monika, A. Taneja, N. Saluja and S. Kumar, "Reconfigurable Antennas for Future Wireless Communication: An Analytical Review," 2022 *IEEE Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, Gwalior, India, 2022, pp. 1-6.

[6] S. Li and H. J. Lee, "GFAM: A Gender-Preserving Face Aging Model for Age Imbalance Data," *Electronics*, vol. 12, no. 11. MDPI AG, p. 2369, May 24, 2023.

[7] X. Liu, Y. Zou, H. Kuang, and X. Ma, "Face Image Age Estimation Based on Data Augmentation and Lightweight Convolutional Neural Network," Symmetry, vol. 12, no. 1. *MDPI AG*, p. 146, Jan. 10, 2020.

[8] W. Wan and H. J. Lee, "A Joint Training Model for Face Sketch Synthesis," *Applied Sciences*, vol. 9, no. 9. MDPI AG, p. 1731, Apr. 26, 2019.

[9] R. Rathore, H. Yennapusa, S. Kumar, M. Mahawar, S. Miglani and G. Sharma, "Cutting-Edge Skin Cancer Detection in a Smart Ecosystem," 2023 *International Conference on Smart Devices (ICSD)*, Dehradun, India, 2024, pp. 1-5.

[10] Ye Sun, Jian-Ming Zhang, Liang-Min Wang, Yong-Zhao Zhan and Shun-Lin Song, "A novel method of recognizing ageing face based on EHMM,"2005 *International Conference on Machine Learning and Cybernetics*, Guangzhou, China, 2005, pp. 4599-4604 Vol. 8.

[11] L. Boussaad and A. Boucetta, "The aging effects on face recognition algorithms: the accuracy according to age groups and age gaps,"2021 *International Conference on Artificial Intelligence for Cyber Security Systems and Privacy (AI-CSP)*, El Oued, Algeria, 2021, pp. 1-6.

[12] J. Suo, X. Chen, S. Shan, W. Gao and Q. Dai, "A Concatenational Graph Evolution Aging Model," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 11, pp. 2083-2096, Nov. 2012.

[13] Shrivastava, R. K., & Rathore, R. (2024). Analysis of Single Server Markovian Queueing Model with Differentiated Working Vacation, Vacation Interruption, Soft Failure, Reneging of Customers.*International Journal for Global Academic & Scientific Research*,3(3), 01–13.

[14] A. M. Osman and S. Viriri, "Face verification across age progression: A survey of the state-of-the-art,"2018 Conference on *Information Communications Technology and Society (ICTAS)*, Durban, South Africa, 2018, pp. 1-6.

[15] Pratap Singh Rathore, S. (2023). The Impact of AI on Recruitment and Selection Processes: Analysing the role of AI in automating and enhancing recruitment and selection procedures. *International Journal for Global Academic & Scientific Research*, 2(2), 51–63.

[16] J. Zhao, S. Yan and J. Feng, "Towards Age-Invariant Face Recognition," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 1, pp. 474-487, 1 Jan. 2022.

[17] Y. Fu, G. Guo and T. S. Huang, "Age Synthesis and Estimation via Faces: A Survey," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 11, pp. 1955-1976, Nov. 2010.

[18] S. P. S. Rathore, J. Patole, G. Tilak, R. Lenka, J. C. Lopez and Priyanka, "Consumer Sentiment Analysis," 2023 *International Conference on Smart Devices (ICSD)*, Dehradun, India, 2024, pp. 1-5.

[19] G. Antipov, M. Baccouche and J. L. Dugelay, "Face aging with conditional generative adversarial networks,"2017 IEEE *International Conference on Image Processing (ICIP)*, Beijing, China, 2017, pp. 2089-2093.

[20] Y. Wu, L. Du and H. Hu, "Parallel Multi-Path Age Distinguish Network for Cross-Age Face Recognition," in IEEE *Transactions on Circuits and Systems for Video Technology*, vol. 31, no. 9, pp. 3482-3492, Sept. 2021.

[21] Ya Su, Mengyao Wang and Hong Bao, "Age-variation face recognition based on bayes inference,"2015 12th *International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, Zhangjiajie, 2015, pp. 1108-1112.

[22] Kaushik, P. (2024). Dynamic Data Scaling Techniques for Streaming Machine Learning. *International Journal for Global Academic & Scientific Research*, 3(1), 1–12.

[23] A. Genovese, V. Piuri and F. Scotti, ”Towards Explainable Face Aging with Generative Adversarial Networks,”2019 IEEE *International Conference on Image Processing (ICIP)*, Taipei, Taiwan, 2019, pp. 3806-3810.

[24] R. Rathore, P. Kaushik, S. S. Sikarwar, H. Joshi, A. K. Mishra and Y. Hudda, ”Intelligent Transportation Systems Make Use of Fog and Edge Computing for Navigation,” 2024 IEEE *International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, Gwalior, India, 2024, pp. 1-6.

[25] Y. Somada, W. Ohyama and T. Wakabayashi, ”Age-Invariant Person Identification by Segmentation Verification of Face Image,”2017 *4th IAPR Asian Conference on Pattern Recognition (ACPR), Nanjing, China*, 2017, pp. 358-363.

[26] M. A. Iqbal, W. Jadoon, and S. K. Kim, “Synthetic Image Generation Using Conditional GAN-Provided Single-Sample Face Image,” *Applied Sciences*, vol. 14, no. 12. MDPI AG, p. 5049, Jun. 10, 2024.

[27] Y. Wang, S. Bai, X. Wan and F. Chen, ”Cross-age face recognition for face images in digital archives,”2023 4th *International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT)*, Nanjing, China, 2023, pp. 315-31910.1109/AINIT59027.2023.10212553.

[28] C. Korgialas, E. Pantraki, A. Bolari, M. Sotiroudi, and C. Kotropoulos, “Face Aging by Explainable Conditional Adversarial Autoencoders,” *Journal of Imaging*, vol. 9, no. 5. MDPI AG, p. 96, May 10, 2023.

[29] M. Verma, A. Kumar and S. Kumar, ”Medical Waste Classification using Deep Learning and Convolutional Neural Networks,” 2022 IEEE Conference on *Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, Gwalior, India, 2022, pp. 1-5.