International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Smart Surveillance for Finding Missing Person

[1]M. PARIMALA
Associate Professor Dept. of Computer Science and Engineering
Vignan's Institute of Management and Technology for Women, Hyd
Email: parimala@vmtw.in

[2]E.S.Akhila
UG Student, Dept. Computer Science and Engineering
Vignan's Institute of Management and Technology for Women, Hyd.
Email: akhila.es2004@gmail.com

[3]A.Varshini
UG Student, Dept. Computer Science and Engineering
Vignan's Institute of Management and Technology for Women, Hyd.
Email: varshinireddyanumula@gmail.com

[4]Ch.Amogha
UG Student, Dept. Computer Science and Engineering
Vignan's Institute of Management and Technology for Women, Hyd.
Email: amoghasrinivas23@gmail.com

Abstract-- **The identification of missing persons remains one of the most challenging tasks for law enforcement and humanitarian organizations worldwide. Traditional methods, which rely heavily on manual visual inspection and outdated biometric data, are often time-consuming, inefficient, and prone to human error. In recent years, the rapid advancement of artificial intelligence (AI), particularly deep learning, has shown significant potential in automating and improving the accuracy of missing person identification. This research explores the integration of deep learning methodologies—specifically convolutional neural networks (CNNs), facial recognition systems, and generative adversarial networks (GANs)—to develop a robust framework for identifying missing individuals from diverse and dynamic sources, such as surveillance footage, social media images, and official databases. This study concludes that deep learning offers a transformative approach to missing person identification by automating recognition tasks, improving matching precision, and enabling scalability across large datasets. It also highlights the ethical and privacy concerns involved in deploying AI-based surveillance systems and advocates for the responsible use of biometric technologies. Future work includes expanding the system to support multimodal data (e.g., voice, gait, text), crossborder interoperability, and integration with mobile applications for broader public engagement in locating missing persons.**

Keywords—Deep Learning, Missing Person Identification, Facial Recognition, Face matching, Age Progression, Transfer Learning.

I. INTRODUCTION

Identifying missing persons is one of the most challenging tasks for law enforcement and humanist organizations around the world. Traditional methods that rely on manual visual inspections and outdated biometric data are often time-consuming, inefficient, and prone to human error. In recent years, rapid advances in artificial intelligence (AI), particularly deep learning, have shown the important potential of automating and improving accuracy in missing person identification. This study examines the integration of depth learning methods, particularly foldable networks (CNNS), facial recognition systems, and generative, rog-harmed networks (geese). This study concludes that by enabling automated recognition tasks, appropriate accuracy improvements, and scalability of large data sets, it provides a transformative approach to identifying human shortages. Ethical and data protection concerns regarding the provision of AI-based surveillance systems and supporters also highlight supporters for the responsible use of biometric technology. Future work will include expanding the system to support multimodal data (voice, gangster, text, etc.), interoperability between operators, and integration into mobile applications for broader general involvement in localizing missing persons. Introduction: The topic of missing persons is a permanent global concern that affects millions of individuals and families each year.

An international report from
Hundreds of thousands of people have been reported by people due to a variety of situations, including natural disasters, armed conflict, human trafficking, aging, and mental issues. The process of identifying and localizing these people is more accurate due to the large number of cases, limited resources, and the lack of current identification data, including manual photo agreements, ophthalmological accounts, and forensic techniques. Error or aggressive, or AGN agents use agn agents, especially if they no longer grow. In recent years, the advent of artificial intelligence (AI) and deep learning have introduced new opportunities to automate and promote the accuracy of identification systems. Deep learning, in particular folding networks (CNNS), has achieved notable success in computer vision tasks such as object recognition, face recognition, and image classification. These progress offers the possibility to create intelligent systems that can analyze and match images of missing persons, even in challenging conditions such as inferior photos, occlusions, and age-related facial changes.
rescue activities. However, facial recognition and the use of AI in this sensitive context also address important ethical and legal considerations, such as data protection concerns, consent, data security, and risk of distortion in algorithmic decisions. These topics need to be considered carefully to ensure the responsible and fair use of the technology. This project/paper examines the design, functionality and effectiveness of intelligent surveillance systems in the localization of missing persons.

II. LITERATURE REVIEW

Schroff et al. [1] We proposed a spatial system that learns the allocation of face images to compact Euclidean spaces, where distance corresponds directly to a measure of facial similarity. This approach allows for accurate facial recognition, cluster formation and review.
Taigman et al.
[2] introduced Deepface, a deep learning-based system that can use 3D and neuronal networks to bridge the gap between human and machine performance in facial testing.
Parkhi et al.
[3] presented a system with a large folding neural network (CNNS) to achieve high level accuracy of face identification tasks. Masi et al.
[4] A reviewed strategy to improve facial recognition in non-disabled environments, including variations in pose, lighting, and expression. They emphasized data enhancement and synthetic generation as impor
[5] Li et al. Zhang et al.
[6] Cascade foldable folding network (mtcnn), a deep network architecture for joint recognition and orientation of common networks.
その高速と精度により、普及しています。

[7] Applies to actual identification systems. Redmon et al.
presented the Yolo framework (only viewed once) for object **recognition. King**

[8] has developed the DLIB face recognition library. This uses a residual metric learning approach to generate 128 dimensions of embedding that allows for effective face comparisons. The FACE_RECOGNITION-API based on this library allows developers to integrate facial adaptation with minimal effort, making it suitable for Python-based systems
[9]. Szegedy et al.
[10] We have introduced an inception network that optimizes computational resources and maintains high identification performance at the same time. These architectures were used in several facial recognition tasks for mobile and embedded applications. K. He et al.
[11] proposed a rest learning frame that facilitates training of very deep networks that are often used in facial function extraction pipelines. Baltrusaitis et al.
[12] discussed behavioral analysis related to improved identification through the integration of visual and context-related notes for multimodal machine learning for emotional computing and missing persons. Don et al. Zhao You are al.

III METHODOLOGY

The methodology for a missing person AI project involves a systematic, multi-layered approach that integrates cutting-edge technologies. Initial steps focus on robust data collection from diverse sources, including surveillance footage, social media, and news articles. This data undergoes thorough pre-processing to ensure consistency and quality, setting the foundation for subsequent analysis. The core of the methodology lies in the application of machine learning algorithms, particularly those specializing in image recognition. Through training on extensive datasets, these algorithms become adept at identifying key features like facial characteristics and contextual cues in surveillance footage. Concurrently, natural language processing techniques analyse textual information, extracting relevant details such as locations and timestamps from news articles and social media posts. The integration of these machine learning and NLP components forms a cohesive AI system capable of processing both visual and textual data. The system continuously refines its understanding through iterative learning, adapting to evolving patterns and improving accuracy over time. Collaboration with law enforcement agencies ensures the validation and enhancement of the system effectiveness in real-world scenarios. In the final stages, the AI system generates actionable insights and potential leads, presenting them to human investigators for validation and decision-making. This human-AI synergy optimizes the overall search and rescue process, harnessing the strengths of automated algorithms and human intuition for an effective and dynamic approach to finding missing persons.

A. SYSTEM ARCHITECTURE

The proposed system's architecture is designed for efficient real-time face recognition and alert notification, as depicted in Figure.1.

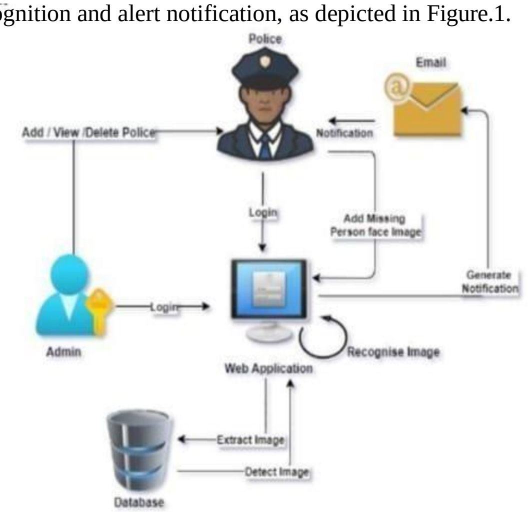

Fig.1: System Architecture

The architecture consists of interconnected modules responsible for data acquisition, processing, recognition, an
d communication.

a. **Data Acquisition Module:** The Data Acquisition Module serves as the foundation of the missing person identification system. It is responsible for collecting, aggregating, and managing facial image data and relevant metadata from various sources. The accuracy and effectiveness of the deep learning models largely depend on the quality, diversity, and volume of data ingested at this stage.

b. **Preprocessing Module:** The Preprocessing Module is a critical component that prepares raw image data for feature extraction and deep learning-based facial recognition. The images collected from various sources are often inconsistent in quality, format, size, and lighting. This module ensures that all inputs are standardized, clean, and suitable for processing by deep learning models, thereby significantly improving system accuracy and efficiency.

c. **Feature Extraction Module:** The Feature Extraction Module is the core of the deep learning pipeline. It converts preprocessed facial images into compact, high-dimensional representations known as embeddings, which capture the unique features of each individual's face. These embeddings are used in the subsequent matching process to identify or verify missing person.

d. **Matching & Similarity Comparison Module:** The Matching & Similarity Comparison Module is responsible for identifying whether a newly acquired facial image (probe) matches any of the faces stored in the database of missing persons. It performs comparisons between feature embeddings generated by the Feature Extraction Module and makes a decision based on similarity thresholds.

e. **User Interface (UI) or Frontend Module:** The User Interface (UI) or Frontend Module is the visual and interactive layer of the system. It allows various stakeholders—such as law enforcement, NGOs, the public, and system administrators—to interact with the system efficiently. The frontend is designed to be intuitive, responsive, and informative, offering real-time access to missing person data, search results, and system status.

IV RESULT AND ANALYSIS

Home page of missing person

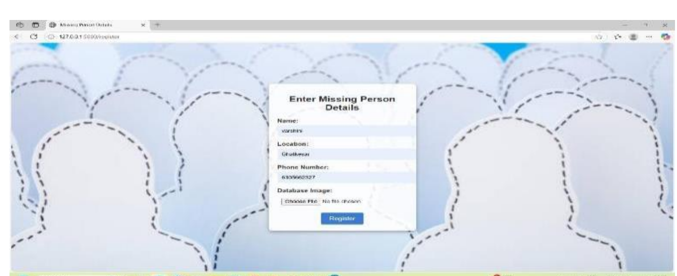

Fig 2 – Details of missing person

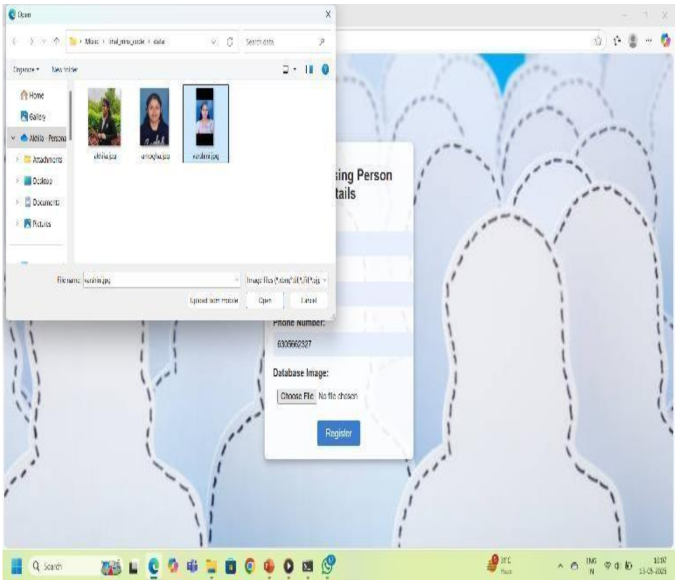

Fig 3- Uploading image of missing person

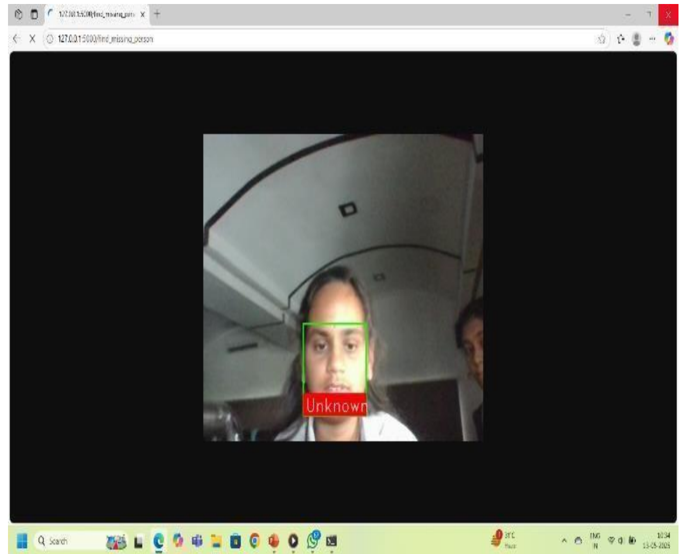

Fig 6 – Unknown Person

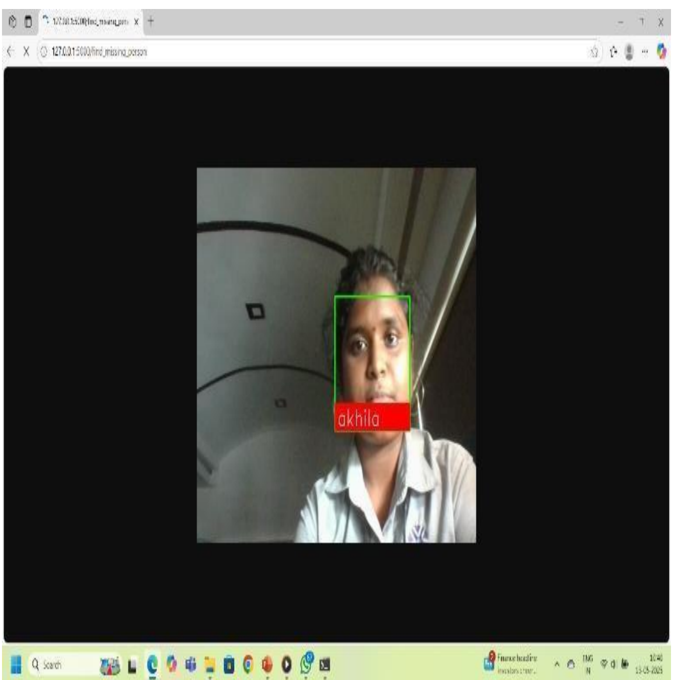

Fig 4- Image of Missing person 1

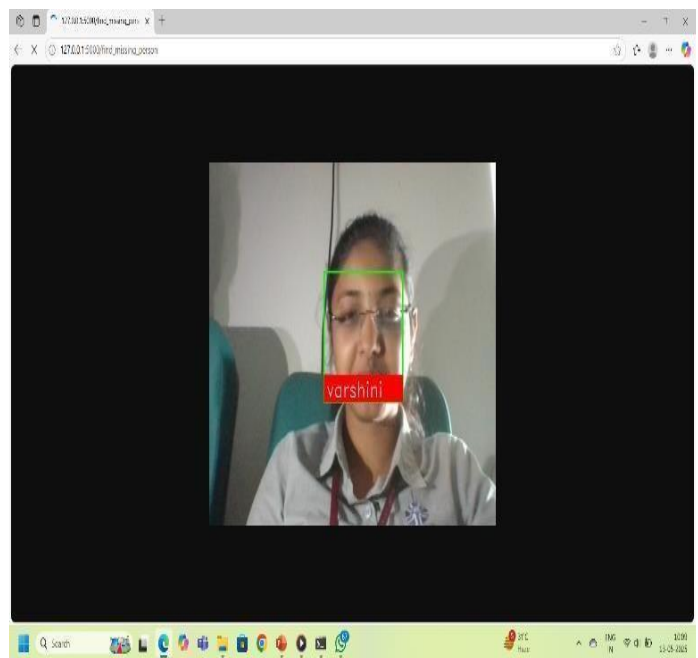

Fig 7– Image of Missing person 2

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

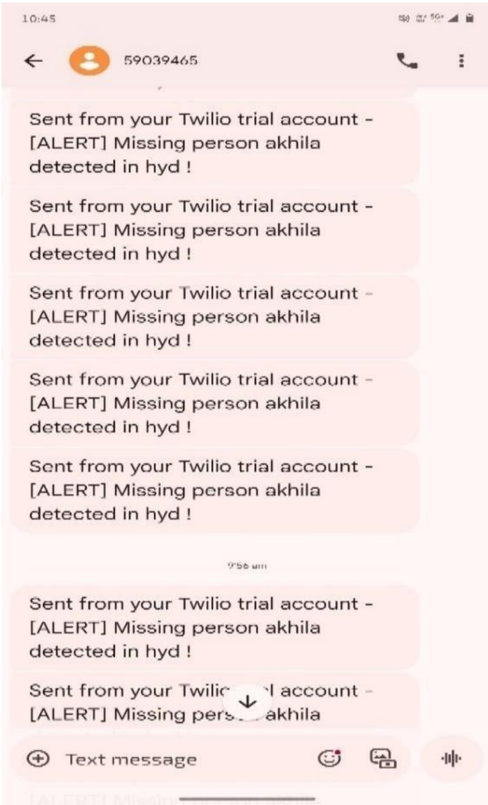

Fig 5 – Message of missing person 1

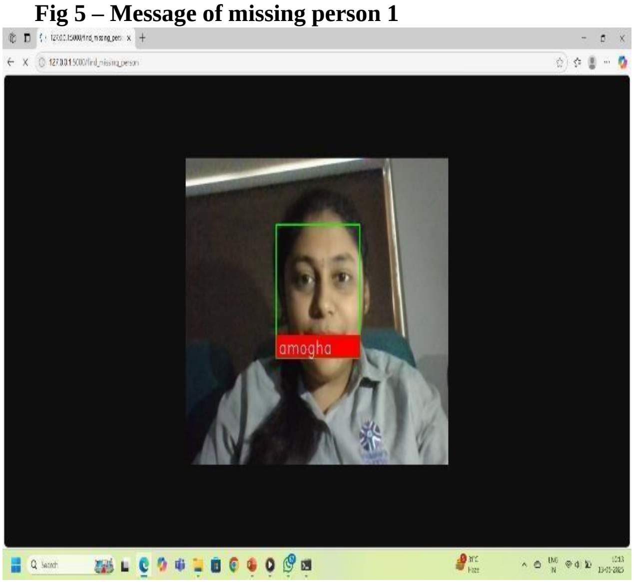

Fig 9– Image of Missing person 3

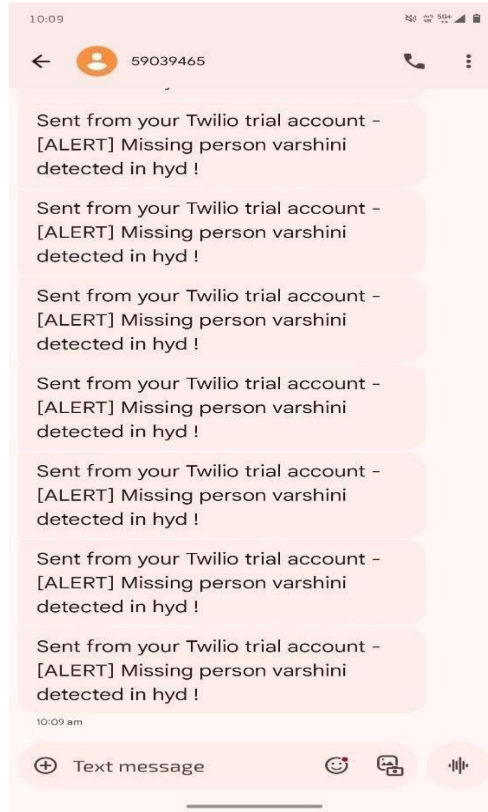

Fig 8– Message of missing person 2

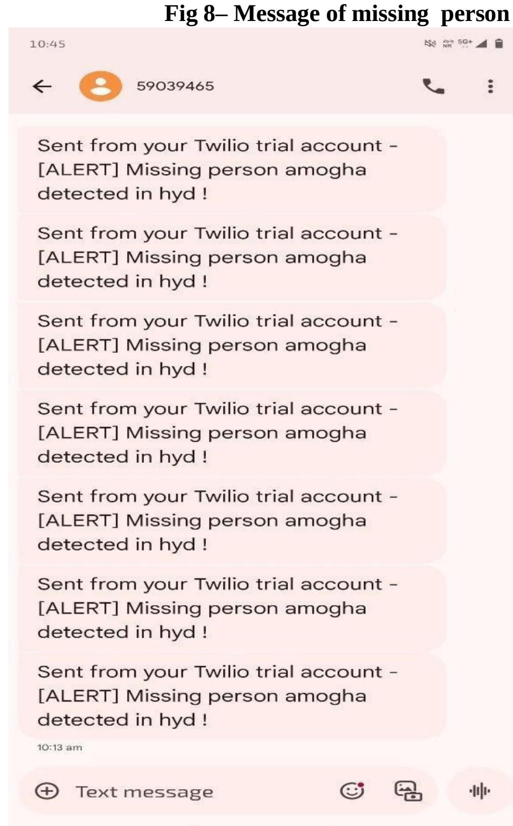

Fig 10 – Message of missing person 3

CONCLUSION

The application of deep learning techniques for missing person identification holds significant promise in addressing one of society's critical challenges. By leveraging advanced facial recognition models, robust data preprocessing, and efficient similarity matching algorithms, the system can accurately and rapidly identify missing individuals from large and diverse datasets. The integration of a userfriendly interface ensures accessibility for law enforcement, NGOs, and the public, facilitating timely intervention and reunification efforts. However, the success of such systems depends heavily on the quality and diversity of collected data, ongoing model refinement, and strict adherence to ethical and privacy standards. Future enhancements may include real-time video analysis, multi-modal data integration, and broader community involvement to improve identification rates further. Overall, deep learning-powered missing person identification systems represent a transformative step forward in enhancing public safety, providing critical support to families, and strengthening law enforcement capabilities looking forward, continuous improvements in deep learning architectures, real-time processing capabilities, and integration of multi-modal biometric data such as voice and gait recognition could further augment the accuracy and reliability of missing person identification systems.

VI FUTURE SCOPE

The field of missing person identification using deep learning continues to evolve rapidly, offering numerous opportunities for enhancement and expansion. Future developments could focus on integrating multi-modal biometric data, such as voice recognition, gait analysis, and iris scanning, to complement facial recognition and increase identification accuracy in challenging conditions where face visibility is limited. Incorporating real-time video analytics from surveillance systems and mobile devices could enable continuous monitoring and instant alerts, significantly reducing the time taken to locate missing individuals. advance in federated learning and privacypreserving AI techniques promise to enhance data security by allowing models to be trained across distributed datasets without compromising individual privacy. This would facilitate collaboration across different law enforcement agencies and organizations while adhering to strict data protection regulations.

VII REFERENCES

[1] F. Schroff, D.Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2015, pp. 815–823.
[2] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the gap to human-level performance in face verification," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2014, pp. 1701–1708.
[3] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition," in Proc. Brit. Mach. Vis. Conf. (BMVC), 2015, pp. 1–12.
[4] I. Masi, A. T. Tran, T. Hassner, J.Leksut, and G. Medioni, "Do we really need to collect millions of faces for effective face recognition?" in Proc. Eur. Conf. Comput. Vis. (ECCV), 2016, pp. 579–596.
[5] H. Li, Z. Lin, X. Shen, J. Brandt, and G. Hua, "A convolutional neural network cascade for face detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2015, pp. 5325–5334.
[6] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, "Joint face detection and alignment using multitask cascaded convolutional networks," IEEE Signal Process. Lett., vol. 23, no. 10, pp. 1499–1503, Oct. 2016.
[7] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR),
[8] D. E. King, "Dlib-ml: A machine learning toolkit," J. Mach. Learn. Res., vol. 10, pp. 1755–1758, 2009.
[9] Ageitgey, A., "face_recognition: Simple face recognition library for Python," GitHub repository, 2017. \[Online]. Available: https://github.com/ageitgey/face_recognition
[10] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, and S. Reed, "Going deeper with convolutions," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2015, pp. 1–9.
[11] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 770–778.
[12] T. Baltrušaitis, C. Ahuja, and L.-P. Morency, "Multimodal machine learning: A survey and taxonomy," IEEE Trans. Pattern Anal. Mach. Intell., vol. 41, no. 2, pp. 423–443, Feb. 2019.