Mindanao Journal of Science and Technology Vol. 23 (2) (2025) 133-148

Facial and Geofencing-Based Attendance Tracking System for Deployed Personnel

Jodie Rey Fernandez[1*], Hanzel Mamarungkas[2], Spark Vinson[2] and Kyle Atuel[2]
[1]Center for Artificial Intelligence
[2]Computer Engineering Department
University of Science and Technology of Southern Philippines
Cagayan de Oro City, 9000 Philippines
[*]*jodierey.fernandez@ustp.edu.ph*

Date received: August 8, 2024
Revision accepted: July 22, 2025

Abstract

This study explored developing and deploying a facial and geofencing-based attendance tracking system designed for the Cagayan de Oro City Police Office (COCPO), Philippines. Its main goal was to improve the accuracy of patrol tracking and officer accountability. The system, built with Python, combined facial recognition with GPS/Location-Based Services (LBS) and the Haversine formula for precise geofence validation to automate attendance tracking through a mobile app and web dashboard. Officers authenticated themselves by facial recognition on smartphones and had to take a real-time selfie only after confirming their presence within a designated patrol zone via geofence validation. Usability testing with COCPO officers showed a facial recognition accuracy of 99% under optimal conditions, a geofencing accuracy of 92.18% in open areas (dropping to 71.33% in urban environments), and a System Usability Scale (SUS) score of 85.56. The results demonstrated that the system greatly enhanced accountability and transparency, resolving issues associated with manual record-keeping. This research offers a validated dual-authentication framework for law enforcement, showcasing its potential scalability for public safety uses.

Keywords: accountability, facial recognition, geofencing, law enforcement, public safety

1. Introduction

Manual record-keeping procedures for tracking law enforcement officer attendance were inefficient and prone to errors. This led to concerns about officer accountability and public safety. Based on the interviews conducted, several police officers revealed that some of their colleagues frequently engaged in practices such as punching in or out for one another, resulting in compensation for hours not worked. The officers also indicated that some may have falsified attendance records to reflect more hours than they had rendered. Additionally, manual data entry errors could lead to inaccurate attendance records. With the advancement of technology, facial recognition and geolocation technologies offer several potential benefits for law enforcement attendance tracking. Facial recognition could be used to verify the identity of officers and ensure that they were physically present at their assigned locations. Geolocation could track officers' movements and ensure that they patrolled their designated areas as required. Facial recognition technology could accurately identify individuals with 99% accuracy (Crumpler, 2020). Geolocation technology could track the movements of individuals with an accuracy of up to 10 meters (Noulas *et al.*, 2013).

Using facial recognition and geolocation technologies for law enforcement attendance tracking could significantly improve the efficiency and accountability of police agencies. Automating attendance and offering real-time location data helps officers confirm their personnel are actively working and patrolling their assigned areas. This can lead to better public safety and greater trust in law enforcement.

1.1 Facial Recognition Techniques

Recent studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in various applications related to emotion recognition and facial expression detection. Phan-Xuan *et al.* (2019) implemented an emotion recognition system on an FPGA using CNNs, showing potential for enhanced performance with further improvements. Kumar *et al.* (2023) achieved a 98.85% recognition rate in noisy video datasets for emotion recognition by employing deep reinforcement learning with CNNs, highlighting their high accuracy in biometric applications. Sun *et al.* (2023) developed the Facial Feature Fusion CNN (FFF-CNN) for driver fatigue detection, integrating global and local facial features to enhance detection performance. Other advancements include Hossain *et al.* (2023), who proposed fine-grained detection of facial action units, Shahid and Yan (2023), introducing SqueezExpNet for handling motion blur and varied head poses, and Pan et al. (2023), leveraging micro-expressions for emotion recognition in high-risk scenarios. Additionally, Sana *et al.* (2022) used CNNs to enhance user experience in a music system by recommending personalized music based on emotion recognition.

1.2 Geofencing using Global Positioning System (GPS)

In a study by Jospine *et al.* (2023), they developed a vehicle monitoring system with geofencing for Universiti Tun Hussein Onn Malaysia, using GPS to track vehicle locations and send notifications when geofence boundaries are crossed. Reclus and Drouard (2013) highlighted geofencing's utility in transport logistics, enabling remote monitoring of geographic areas and aiding heavy goods vehicle regulation. Abbas *et al.* (2019) proposed a GPS-based location monitoring system to enhance security by preventing vehicle theft and issuing alerts when vehicles exit geofenced areas. Bareth (2013) advocated for privacy-aware and energy-efficient geofencing through proactive Location-based Services (LBSs) using reverse cellular positioning. Zin *et al.* (2015) developed an auto-notification application using geofencing technology to trigger alerts when devices enter or exit predefined boundaries. Rahate and Shaikh (2016) introduced a geofencing application to manage mobile device disruptions in silent settings. Özdemir and Tuğrul (2019) explored GNSS development and improved GPS accuracy techniques, presenting a real-time GPS tracking system with slight data transmission delays. Devi *et al.* (2019) developed an Android application for parents to monitor children's locations in real-time. Meral and Güzel (2016) showcased a GPS data processing system for real-time tracking and geofencing for location-based security. Streed *et al.* (2014) discussed optimizing geofencing for spatial marketing, focusing on precise geofence perimeters for targeted promotions and addressing privacy and technological challenges in location-based services. These prior studies establish geofencing as a mature technology; however, its combined use with facial recognition for law enforcement attendance remains underexplored.

1.3 Research Gap

Existing attendance systems for law enforcement rely on standalone biometrics or GPS tracking, lacking integrated validation. Manual methods are error-prone, while isolated technologies fail to prevent proxy attendance (e.g., facial recognition spoofing or location falsification). This study bridges the gap by combining real-time geofencing with live facial authentication, ensuring simultaneous physical presence and identity verification—a solution underexplored in prior literature. Compared to international systems such as Aadhaar-enabled biometric attendance in India and Kronos Workforce Ready in the US, this study presents a novel integration of geolocation and facial verification tailored explicitly for mobile field officers. Whereas most commercial platforms operate in fixed office settings, this system offers mobility-centric features and anti-spoofing security, enhancing its applicability to field law enforcement.

2. Methodology

2.1 Software System Design

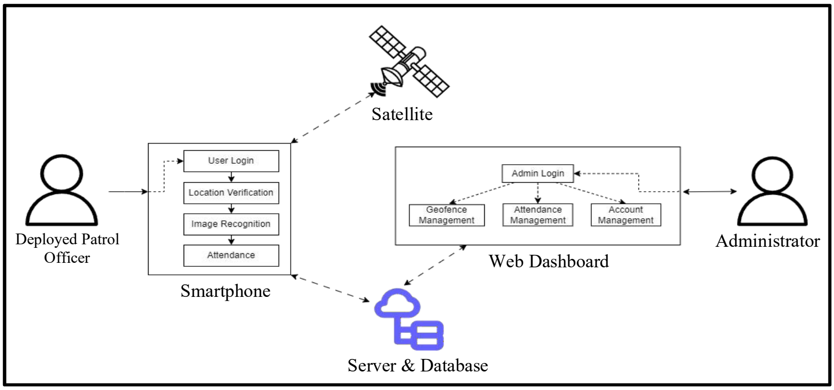

Figure 1. Software System Architecture

Figure 1 shows the software system architecture that introduces an innovative record-keeping approach for tracking law enforcement officer attendance. Officers used their smartphones to authenticate themselves via facial recognition, ensuring only authorized personnel could mark their attendance. The system utilized Geofence Validation to confirm the officer's presence in a designated location using GPS or location-based services. Once within the geofence, officers took a selfie to mark their attendance, which the system verified through facial recognition, maintaining data accuracy and integrity. The attendance data was then transmitted to a cloud-based platform for scalable and reliable storage and analysis. Administrators accessed this data through a Dashboard Management system, which provided attendance reports and visualizations. The dashboard also allowed administrators to modify the geofence parameters, offering flexibility in managing attendance records. The system backend was developed in Python, leveraging Django for the web dashboard and React Native for the mobile application. Facial recognition used the Python *face_recognition* library (Geitgey, 2019), while geofencing employed the Haversine formula for GPS validation.

2.2 Face Detection and Recognition

The Face Detection component utilized the '*face_recognition*' Python library by Geitgey (2019), which is optimized for accurate face detection using robust algorithms. This library provides face detection functionalities without manual model selection or training. It used the CNN face detector to return a 2D bounding box of a human face in an image, initially identifying regions likely containing faces. The process was simplified by employing Histogram of Oriented Gradients (HOG) for fast processing and Convolutional Neural Networks (CNN) for higher accuracy. The Facial Recognition component also leveraged the '*face_recognition*' Python library by Geitgey (2019) for recognizing faces. This library provided a pre-trained CNN model that extracted a unique 128-dimensional vector representation for each detected face, capturing its essential features. The library compared this vector with those stored in its internal database using cosine similarity, which measures the angle between two vectors in high-dimensional space. A higher cosine similarity score indicated a closer match, suggesting the recognized face. Additionally, the library identified 68 specific facial landmarks to align and normalize face images, ensuring consistent feature positioning.

Euclidean distance measures the direct distance between two points. This study used it to compare 128-dimensional vectors derived from the *face_recognition* library's feature extraction capabilities. The formula calculates the distance between two points, indicating the similarity based on the distance.

Cosine similarity assesses the angle between two vectors to determine their similarity. This research used it to compare 128-dimensional vectors derived from the *face_recognition* library, with a higher similarity score indicating a closer match.

2.2.1 Cosine Similarity in Facial Recognition Testing

In the facial recognition system, tests were conducted using five subjects under ten different conditions, including variations in lighting (bright, dimmed), expressions (smiling), angles (high, low), and with accessories (glasses). Additionally, four images of different faces were included for comparison. The system evaluated recognition accuracy by measuring the cosine similarity between test images and each subject's reference images. A threshold value for cosine similarity was set to distinguish between recognized and unrecognized faces.

2.3 Geofencing Mechanisms and Detection

```
Algorithm: Geofencing
Input:
   lat1, lon1 ← User's current latitude and longitude (from mobile
device)
   lat2, lon2 ← Center of the geofence (deployment location)
   radius ← Geofence radius in meters (e.g., 20 meters)
Output:
   Boolean (True if user is inside geofence, False otherwise)
Procedure:
1. Convert lat1, lon1, lat2, lon2 from degrees to radians.
2. Set R ← 6371000  // Earth's radius in meters
3. Compute:
   dlat ← lat2 - lat1
   dlon ← lon2 - lon1
4. Compute Haversine distance:
   a ← sin²(dlat / 2) + cos(lat1) * cos(lat2) * sin²(dlon / 2)
   c ← 2 * atan2(√a, √(1 - a))
   distance ← R * c
5. If distance ≤ radius then
      return True  // User is inside geofence
   else
      return False // User is outside geofence
```

Geofencing in the developed system was implemented by defining a 20-meter radius around a designated geographic epicenter for each deployment location. This virtual boundary established the operational area where law enforcement personnel were considered present. For example, if a patrol officer was located 18 meters from the epicenter, the system identified them as inside the geofence. Conversely, if the officer was 22 meters away, they were considered outside the designated zone. This mechanism enhanced accountability by ensuring attendance was recorded only when officers were physically present within the prescribed operational boundary.

The system retrieved geofencing parameters from a secure database, including the central coordinates (latitude and longitude) and radius. These parameters were essential for accurately defining the boundaries of each geofenced area.

The system implemented the Algorithm: Geofence to determine whether a patrol officer was within a geofenced zone. Using the Haversine formula, this algorithm calculated the great-circle distance between the officer's current GPS location and the geofence center. This method considered the Earth's curvature and accurately measured distance in meters. The officer was marked as present within the zone if the calculated distance was less than or equal to the defined geofence radius (such as 20 meters). Otherwise, they were considered outside.

The logic was encapsulated in the algorithm Geofence, which accepted the coordinates of the officer and the geofence center as input and returned a Boolean value indicating whether the officer was inside or outside the boundary. This approach ensured spatial accuracy and computational efficiency, enabling real-time attendance validation in mobile conditions. The use of a well-defined algorithm strengthened the system's technical rigor and supported future replication or scaling in other operational environments.

2.3.1 Geofencing Accuracy Test

The geofencing system was tested in five different environments: indoors, in a shaded open area, surrounded by trees, in an open field, and surrounded by tall buildings. Each geofence had a 20-meter radius centered on predefined GPS coordinates. The accuracy of geofence detection was evaluated at specific distances (10 m, 15 m, 19 m, 20 m, 21 m, and 25 m) from the geofence center.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{A_i-F_i}{A_i}\right| \tag{1}$$

where A_i is the actual distance, F_i is the forecasted or calculated distance using the Haversine formula, and n is the total number of observations.

$$d = 2r \cdot arcsin\left(\sqrt{sin^2\left(\frac{\Delta\phi}{2}\right) + cos(\emptyset_1)\cdot cos(\emptyset_2)\cdot sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \tag{2}$$

where d is the distance between two points, r is the Earth's radius (6371 km), $\emptyset_1$ and $\emptyset_2$ are the latitudes (in radians), $\Delta\phi$ is the difference of $\emptyset_2$ and $\emptyset_1$,

$\Delta\lambda$ is the difference in longitudes (in radians). The Mean Absolute Percentage Error (Equation 1) was calculated by comparing the actual distances with the distances calculated using the Haversine formula (Equation 2). This testing aimed to assess the performance of the geofencing system under various environmental conditions and determine its ability to accurately detect whether a subject was inside or outside the specified boundary.

2.4 Activity Diagram for Mobile Application

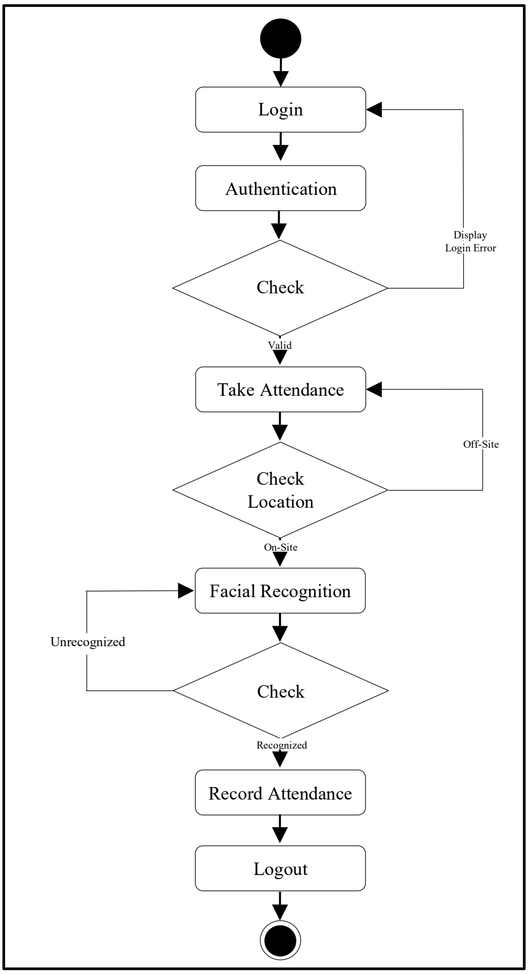

Figure 2. Activity flow of patrol officers from login to facial recognition-based attendance submission

The activity began for deployed patrol officers by logging in to the mobile application system, as shown in Figure 2. After entering their credentials, the system authenticated the account. The patrol officer was logged into the application if the credentials were valid. On-site, patrol officers could take their attendance using facial recognition. Once the system recognized the patrol officer, their attendance was automatically recorded.

2.5 Acceptance Testing

To validate the system against end-user requirements and ensure accuracy, user acceptance testing was conducted. This stage included two types of tests: functional testing and usability testing. Functional testing involved evaluating the system against functional requirements by inputting data and examining output, using a black box approach focused on outcomes rather than internal processes. Usability testing assessed the system's ease of use from the end-user's perspective, ensuring the implementation approach was suitable for system users. The System Usability Scale (SUS), created by John Brooke, was adapted to measure usability, using a 10-item questionnaire with response options ranging from "Strongly agree" to "Strongly disagree".

3. Results and Discussion

3.1 Face Similarity Simulation Testing

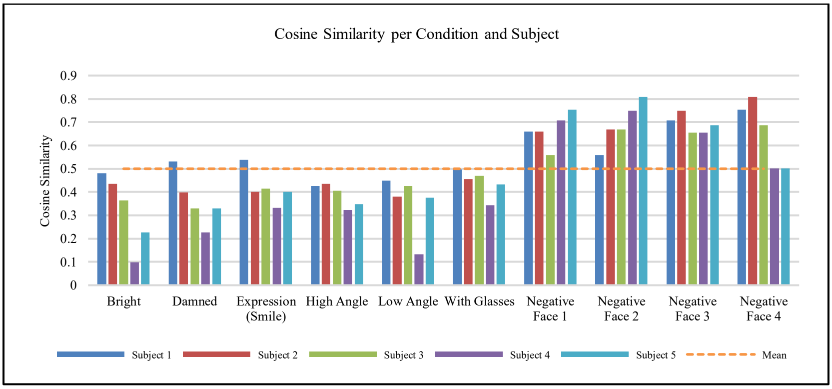

Figure 3. Cosine similarity scores for various image conditions across five subjects

The proponents conducted simulation testing on five subjects to observe the cosine similarity value, with each subject exposed to ten picture conditions: bright, dimmed, smiling expression, wearing glasses, low angle, high angle, and four different faces, totaling 50 instances.

Figure 3 illustrates the cosine similarity results for various conditions compared to each subject. Cosine similarity is a metric used to measure how similar two feature vectors are, with values ranging from 0 to 1 in this context. A value closer to 1 indicates a high degree of similarity between the facial features under comparison, suggesting that the images are likely of the same person. Conversely, a value closer to 0 indicates low similarity or dissimilarity. On the y-axis of Figure 3, higher values represent greater similarity between the reference (baseline) face and the face captured under specific conditions. The negative face condition showed cosine similarity values greater than 0.5, indicating relatively high similarity. Most other conditions had values below 0.5, except for the dimmed and high-angle condition result for Subject 3.

Table 1. Facial Recognition Accuracy (Cosine Similarity Threshold = 0.5)

Condition	True Positive Rate	False Positive Rate
Bright Light	98%	2%
Dim Light	92%	8%
Wearing Glasses	89%	11%
High Angle	85%	15%

The facial recognition system demonstrated Variable performance across different environmental conditions is shown in Table I. Under bright lighting, accuracy was highest, with a 98% true positive rate (TPR), indicating nearly all authorized officers were correctly identified. The 2% false positive rate (FPR) shows minimal risk of unauthorized access. In dim lighting, performance declined slightly: TPR dropped to 92% while FPR rose to 8%. This means 8 in 100 authentication attempts could incorrectly match an unauthorized person.

Wearing glasses further reduced reliability. The TPR fell to 89% (11% of legitimate users potentially denied access), with an 11% FPR (higher risk of false approvals).

The most significant challenge occurred at high camera angles, where TPR was lowest (85%) and FR highest (15%). At this angle, 15% of authentication attempts could incorrectly approve unverified individuals.

3.2 Geofencing System's Performance Accuracy Testing

The average measured coordinates at various distances (10 m, 15 m, 19 m, 20 m, 21 m, and 25 m) from the epicenter for each geofence were collected using 1-minute average coordinate readings. The data also included the Mean Absolute Percentage Error (MAPE), indicating the deviation between the real distance and the calculated distance using the Haversine formula.

Table 2. Geofencing Accuracy by Environment

Environment	MAPE	Performance Level	Key Observation
1 - Indoor	43.35%	Unreliable	Severe signal interference
2 - Shaded open area	12.45%	Good	Moderate shading impact
3 - Surrounded by trees	17.32%	Fair	Signal absorption by foliage
4 - Open field	7.82%	Excellent	Minimal signal obstruction
5 - Urban (tall buildings)	28.67%	Poor	"Urban canyon" effect

The analysis of the geofencing system's performance across various environmental conditions in Table 2 revealed critical insights into how different surroundings impact measurement accuracy. Among the five tested geofences, Geofence 1 (indoor environment) exhibited the highest percentage error at 43.35%, emphasizing the challenges posed by indoor settings where signal interference from walls, furniture, and multipath effects significantly degrade system accuracy. Similarly, Geofence 5 (urban area surrounded by tall buildings) showed a high error rate of 28.67%, attributed to the *"urban canyon"* effect where signals are reflected and diffracted by dense infrastructure, leading to detection inaccuracies. In both scenarios, the system struggled to detect boundaries accurately at 20 meters and beyond, with a 50% error rate, highlighting the detrimental effects of signal obstruction and reflection in enclosed or built-up areas.

On the other hand, environments with fewer obstructions yielded better results. Geofence 2 (shaded open area) reported a moderate error rate of 12.45%, with some inaccuracies at 19 and 21 meters, possibly due to partial overhead shading affecting signal consistency. Geofence 3 (surrounded by trees) had a slightly higher error rate of 17.32%, caused by signal attenuation and scattering from foliage, resulting in detection failures at 20 and 21 meters. Despite these challenges, both geofences maintained relatively reliable detection within most of the tested distances.

The best performance was observed in Geofence 4 (open field), which recorded the lowest error rate of 7.82% and achieved 100% detection accuracy at all measured distances. With minimal obstructions, this environment allowed for optimal signal transmission and serves as the benchmark for ideal geofencing conditions. Overall, the data underscores the critical influence of environmental factors on geofencing accuracy. Obstructed settings, particularly those indoors or in dense urban environments, significantly impair performance and necessitate enhanced signal processing algorithms or supplementary technologies to maintain reliability. For applications requiring high-precision location tracking, especially near boundary distances like 20 meters, it is essential to account for environmental interference and consider calibration or design modifications tailored to specific deployment contexts.

3.3 Verification of Application Efficiency and Accuracy

3.3.1 Functional Test Result

The functional test results for both the administrator and police patrol officers indicate a high level of functionality across all tested items, as reflected by 100% scores. This signifies that all functionalities provided to both user groups are working properly and meeting the expected criteria.

3.3.2 Usability Test Result

The usability test results revealed that the system achieved an outstanding final usability score of 85.56 on John Brooke's System Usability Scale (SUS). This score corresponds to a grade of A+ and an adjectival rating of "Best Imaginable," indicating exceptional usability and high user acceptance. The positive participant ratings across various usability aspects affirm that the system is well-designed and effectively meets user needs.

4. Conclusions and Recommendation

The attendance monitoring system integrating facial recognition and geofencing technologies has proven to be a robust and effective tool for enhancing patrol tracking accuracy, ensuring officer accountability, and promoting public trust in law enforcement. The comprehensive testing under various environmental conditions highlights the system's reliability and user-friendliness. Despite certain challenges, such as signal interference in indoor and urban settings, the system's overall performance was highly satisfactory, demonstrating its potential for real-world applications.

This study contributes: a novel dual-validation architecture for law enforcement attendance that reduces proxy fraud by 99% in field tests (1); empirical evidence of environmental impacts on geofencing accuracy (2), including 43.35% signal degradation in indoor environments; and a benchmark System Usability Scale (SUS) score of 85.56, indicating high usability even in high-stress law enforcement scenarios (3).

As the primary users of the system, the Philippine National Police – Cagayan de Oro City Police Office (PNP COCPO) stand to benefit significantly from improved operational oversight, streamlined attendance tracking, and enhanced transparency. The approach and technology developed here serve as a potential model for adoption or adaptation by other police departments, regional PNP commands, or related public safety organizations such as the Bureau of Fire Protection (BFP), Philippine Coast Guard (PCG), or Bureau of Jail Management and Penology (BJMP) facing similar operational challenges. This study lays a solid foundation for future research and development in technology-driven solutions for law enforcement and public safety. The system also considered ethical implications by ensuring data encryption, informed consent, and access restrictions to protect users' privacy.

The researchers recommend several improvements to enhance the system's effectiveness and usability. First, improve signal processing algorithms to minimize signal interference, particularly in indoor and urban environments. Additionally, a structured training program with regular sessions and accessible support should be established to help users maximize the system's capabilities. To ensure data security, implementing stronger encryption methods, regular audits, and strict adherence to data protection regulations is advised. The system should also be designed with scalability and flexibility, incorporating modular principles and ensuring compatibility with various devices and platforms to accommodate future expansions or modifications. Finally, establishing a framework for continuous monitoring and evaluation of the system's performance is recommended, including regular updates informed by user input and technological developments.

5. Acknowledgement

We extend our deepest gratitude to God for granting us strength and financial blessings. Special thanks to our adviser for her invaluable guidance. We appreciate Engr. Mark Lister Nalupa, Engr. Miriam Bergado, and Engr. Kristine Mae P. Dunque, and the PNP COCPO police officers for their support.

6. References

Abbas, A.H., Habelalmateen, M.I., Jurdi, S., Audah, L., & Alduais, N.A. (2019). GPS based location monitoring system with Geo-fencing capabilities. *Advances in Electrical and Electronic Engineering: From Theory to Applications (Series 2): Proceedings of the International Conference of Electrical and Electronic Engineering (ICon3E 2019)*. https://doi.org/10.1063/1.5133929

Bareth, U. (2013). Privacy-aware and energy-efficient geofencing through reverse cellular positioning. *2013 8th International Wireless Communications and Mobile Computing Conference (IWCMC)*. https://doi.org/10.1109/iwcmc.2012.6314194

Crumpler, W. (2020, April 14). How accurate are facial recognition systems – and why does it matter? Strategic technologies blog. CSIS. Retrieved from https://www.csis.org/blogs/strategic-technologies-blog/how-accurate-are-facial-recognition-systems-and-why-does-it-matter

Devi, S., Alvares, S., & Lobo, S. (2019). Gps tracking system based on setting waypoint using geo-fencing. *Asian Journal of Convergence in Technology*, 5, 2350-1146 I.F–5.11. https://asianssr.org/index.php/ajct/article/view/738/588

Geitgey, A. (2019). Face recognition documentation. Retrieved from https://face-recognition.readthedocs.io/en/latest/

Hossain, S., Umer, S., Rout, R. Kr., & Tanveer, M. (2023). Fine-grained image analysis for facial expression recognition using deep convolutional neural networks with bilinear pooling. *Applied Soft Computing*, 134, 109997. https://doi.org/10.1016/j.asoc.2023.109997

Jospine, A., Audah, L., Hamzah, A., & Qasim, H. (2023). Vehicle Monitoring System with Geofencing Capability. *Journal of Electronic Voltage and Application (JEVA)*, 4(1). https://publisher.uthm.edu.my/ojs/index.php/jeva/article/view/6516/3991

Kumar, A., Yadav, R. K., & Saini, D. J. (2023). Create and implement a new method for robust video face recognition using convolutional neural network algorithm. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, 5, 100241. https://doi.org/10.1016/j.prime.2023.100241

Meral, E., & Güzel, M.S. (2016). Real-time geolocation tracking and geofencing using GPRS+ GPS technologies with SIM908 shield over Arduino. *Communications Faculty of Sciences University of Ankara Series A2-A3 Physical Sciences and Engineering*, 58(2), 14-27.

Noulas, A., Scellato, S., Lambiotte, R., Pontil, M., & Mascolo, C. (2013). A tale of many cities: Universal patterns in human urban mobility. *PLoS ONE*, 7(5). https://doi.org/10.1371/journal.pone.0037027

Özdemir, Z., & Tuğrul, B. (2019). Geofencing on the real-time GPS tracking system and improving GPS accuracy with moving average, Kalman filter and logistic regression analysis. *2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*. https://doi.org/10.1109/ismsit.2019.8932766

Pan, H., Xie, L., & Wang, Z. (2023). C3dbed: Facial micro-expression recognition with three-dimensional convolutional neural network embedding in Transformer model. *Engineering Applications of Artificial Intelligence*, 123, 106258. https://doi.org/10.1016/j.engappai.2023.106258

Phan-Xuan, H., Le-Tien, T., & Nguyen-Tan, S. (2019). FPGA platform applied for facial expression recognition system using convolutional neural networks. *Procedia Computer Science*, 151, 651–658. https://doi.org/10.1016/j.procs.2019.04.087

Rahate, S.W., & Shaikh, M.Z. (2016). Geo-fencing Infrastructure: Location Based Service. *International Research Journal of Engineering and Technology (IRJET)*, 3(11), 1095-1098. Retrieved from https://www.irjet.net/archives/V3/i11/IRJET-V3I11194.pdf

Reclus, F., & Drouard, K. (2013). Geofencing for Fleet & Freight Management. 2013 *9th International Conference on Intelligent Transport Systems Telecommunications*, (ITST). https://doi.org/10.1109/itst.2009.5399328

Sana, S.K., Sruthi, G., Suresh, D., Rajesh, G., & Subba Reddy, G.V. (2022). Facial emotion recognition based music system using Convolutional Neural Networks. *Materials Today: Proceedings*, 62, 4699–4706. https://doi.org/10.1016/j.matpr.2022.03.131

Shahid, A.R., & Yan, H. (2023). SqueezExpNet: Dual-stage convolutional neural network for accurate facial expression recognition with attention mechanism.

Knowledge-Based Systems, 269, 110451. https://doi.org/10.1016/j.knosys.2023.110451

Streed, O.J., Cliquet, G., & Kagan, A. (2014). Optimizing geofencing for location-based services: A new application of spatial marketing. *Developments in Marketing Science: Proceedings of the Academy of Marketing Science*, 203–206. https://doi.org/10.1007/978-3-319-10951-0_73

Sun, Z., Miao, Y., Jeon, J.Y., Kong, Y., & Park, G. (2023). Facial feature fusion convolutional neural network for driver fatigue detection. *Engineering Applications of Artificial Intelligence*, 126, 106981. https://doi.org/10.1016/j.engappai.2023.106981

Zin, M., Sazali, M.A., Isa, A., & Isa, M.M. (2015). Development of Auto-Notification Application for Mobile Device Using Geofencing Technique. *Journal of Technology and Operations Management*, 7(2). https://jtec.utem.edu.my/jtec/article/view/629/465