A Smart IoT-Based Communication and Optimization System for Hajj and Umrah Services

T. H. F. Harumy[1], M. Gahara[2], M. F. Sipahutar[3], A. Zakiyah[4],
N. A. Hasna[5], E. Ikhsan[6], Yusuf N. Buwono[7], Haposan Delon Pasaribu[8]
Computer Science and Engineering, Universitas Sumatera Utara, North Sumatera, Indonesia[1, 2, 3]
Computer Science, Oxioo Teknologi Indonesia, East Java, Indonesia[4, 5]
Faculty of Law, Universitas Sumatera Utara, North Sumatera, Indonesia[6]
Faculty of Engineering, Universitas Sumatera Utara, North Sumatera, Indonesia[7, 8]

***Abstract*—The management of Hajj and Umrah services requires reliable communication, continuous location awareness, and rapid emergency response because pilgrims move in dense and dynamic environments. This study presents a smart Internet of Things (IoT) based communication and optimization system for Hajj and Umrah services. The system integrates GPS-enabled wearable devices, a panic button emergency mechanism, cellular data transmission, a centralized cloud dashboard, and a network-aware deep neural network (DNN) component for congestion risk prediction. Unlike a purely sensing-oriented tracking system, the proposed framework explicitly incorporates communication indicators, including end-to-end latency, packet delivery ratio, jitter, and bandwidth utilization, as part of the monitoring and prediction pipeline. The prototype was implemented using a wearable tracking device and a web-based dashboard, while the prediction component was evaluated on a simulation dataset containing spatiotemporal mobility and network performance variables. Functional verification produced a black-box functional success rate of 95.6%, which is reported only as an implementation reliability indicator. The congestion risk classifier achieved 80.0% accuracy with macro-averaged precision, recall, and F1 score values of 0.72, 0.77, and 0.74, respectively. The evaluation also defines baseline comparisons, confusion matrix analysis, ROC-based assessment, and network-level stress scenarios to clarify the scientific interpretation of the results. The findings indicate that a network-aware IoT architecture can improve situational awareness and support timely operational decision-making for large-scale pilgrimage services, while full validation still requires larger real-world deployment data.**

***Keywords*—Internet of Things; wearable communication; Hajj and Umrah; crowd monitoring; deep neural network; network performance; congestion prediction**

I. Introduction

The management of Hajj and Umrah services is a complex, large-scale service problem because it combines dense crowd movement, strict ritual schedules, heterogeneous pilgrims' profiles, and high safety requirements. Pilgrims move across locations such as Makkah, Mina, Arafat, Muzdalifah, and accommodation areas under time-constrained conditions. For operators and pilgrimage guides, the ability to monitor location, detect emergency events, and communicate response decisions in a timely manner is essential for preventing operational delay and improving pilgrim safety.

Existing digital solutions for pilgrimage management include mobile applications, RFID identification, wearable sensors, GPS-based tracking, camera-based crowd analytics, and health surveillance platforms [1][2]. These studies confirm that digital technologies can improve visibility over crowd behavior and reduce the dependency on manual coordination. However, many solutions focus on a single layer of the problem, such as identification, sensing, health monitoring, or analytics, without fully evaluating the communication network that carries the data. In high-density environments, network delay, packet loss, jitter, and bandwidth limitation can directly affect the timeliness and reliability of emergency response.

This study clarifies that the main contribution is not a new deep learning algorithm. Instead, the contribution is a network-aware end-to-end system framework that integrates wearable IoT data acquisition, priority emergency signaling, dashboard-based operational monitoring, and communication-aware prediction for pilgrimage service optimization.

The specific contributions of this study are as follows. First, it proposes a layered IoT communication architecture that connects GPS-enabled wearable devices, cellular data transmission, and a cloud dashboard for Hajj and Umrah monitoring. Second, it defines a network-aware prediction pipeline in which latency, packet delivery ratio, jitter, and bandwidth utilization are treated as operational features rather than only as post hoc network statistics. Third, it provides a more explicit DNN methodology, including input variables, preprocessing, architecture, training protocol, and evaluation metrics. Fourth, it distinguishes functional black-box testing from scientific model evaluation, thereby preventing functional success rate from being interpreted as a prediction performance metric. Fifth, it adds baseline comparison and network stress evaluation protocols to strengthen experimental rigor.

The rest of this study is organized as follows. Section II synthesizes related work and identifies the research gap. Section III explains the proposed architecture and methodology. Section IV presents the implementation and evaluation. Section V discusses implications and limitations. Section VI concludes the study and outlines future work.

II. Related Work and Research Gap

Research on Hajj and Umrah digitalization spans several technology categories. Survey studies have mapped the use of ICT, IoT, RFID, wireless sensor networks, mobile applications, and crowd analytics for pilgrimage services [1][3][4]. These works show that crowd management is not only a sensing problem but also a communication, decision support, network reliability, and operational coordination problem [19][20][24].

Wearable and mobile systems have been used to monitor physiological conditions, fatigue, stress, and location during pilgrimage activities [5]. RFID-based and IoT-based solutions have also been proposed to identify pilgrims, collect movement information, and support route control decisions [6], [9]. Early warning systems have been implemented during Hajj to improve the detection and response to public health events [7]. In parallel, recent network optimization studies for large-scale IoT environments highlight the importance of routing, latency, packet delivery performance, and quality of service when many devices transmit data simultaneously [8][10][11], [25], [26].

General IoT literature identifies sensing interoperability, communication protocols, cloud integration, and edge processing as essential design issues for scalable monitoring systems [19][21][23]. Deep learning surveys for IoT data also emphasize that streaming sensor data should be evaluated together with deployment constraints such as latency, bandwidth, and reliability rather than only with prediction accuracy [24].

Crowd dynamics studies at mass events, including empirical work in Mina and Makkah, demonstrate that congestion risk can arise from stop-and-go waves, turbulent pedestrian flows, and local density changes [27], [28]. Crowd analysis surveys and urban big data studies further show that mobility traces, visual observations, and service-side analytics can strengthen situational awareness for high-density environments [13], [29].

Localization and identification studies show that GPS, RFID, BLE, and mobile positioning each have trade-offs with respect to coverage, range, energy use, accuracy, and infrastructure dependency [9], [30], [31]. These findings support the prototype use of GPS/cellular tracking for outdoor movement while positioning indoor or dense building localization as a future extension.

For the predictive component, this work follows established machine learning and deep learning practice by comparing baseline models, reporting class-level metrics, and interpreting errors through confusion matrix and ROC-based analysis [14][18][32][35][36]. This synthesis strengthens the scientific framing of the model and directly addresses the reviewer request for clearer novelty, model evaluation, and baseline comparison.

Despite this progress, three gaps remain relevant. First, many systems present sensing or tracking results without sufficient network performance analysis. Second, AI-based crowd prediction studies often report prediction metrics without explaining how communication delay or packet loss affects the inference pipeline. Third, system prototype papers sometimes mix functional testing with scientific evaluation, making it unclear whether reported success rates represent software reliability, network reliability, or AI model quality. Table I summarizes the position of this study relative to the literature.

TABLE I. Comparative Synthesis of Related Work and Research Gap

Stream	Studies	Strength	Limitation	This study
Hajj/Umrah ICT	[1][4]	Technology taxonomy	Limited end-to-end prototype	Wearable-to-dashboard framework
Wearable/RFID/crowd	[5], [6], [9], [12]	Monitoring and identification	Often limited network analysis	GPS, SOS, and KPI-aware tracking
Network/edge IoT	[8], [13], [19], [19][21][26]	QoS and delivery focus	Often separated from service workflow	Links KPIs to monitoring/prediction.
AI/sequence learning	[14][18], [32][35][37]	Temporal modeling and metrics	Needs transparent baselines	Adds DNN protocol and comparison

III. Proposed Methodology

A. Overall Research Workflow

This study adopts a system-oriented experimental methodology. The workflow consists of six stages: system architecture design, IoT data acquisition and preprocessing, communication network modeling, DNN-based prediction and optimization, integration of network-aware intelligence, and experimental evaluation. Fig. 1 summarizes the revised workflow.

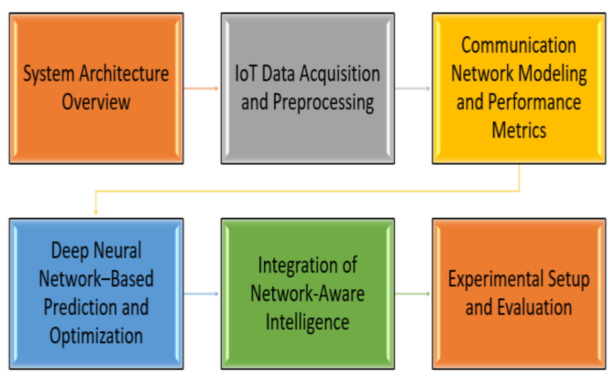
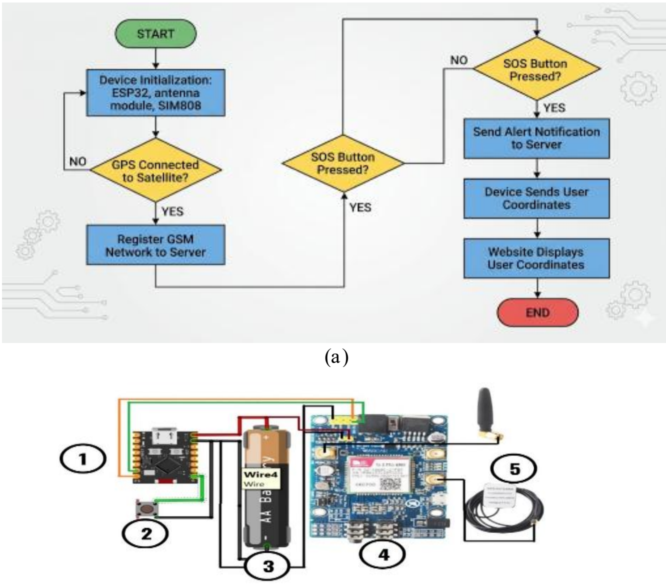


Fig. 1. Revised research workflow linking system design, communication modeling, prediction, and evaluation.

B. System Architecture

The proposed architecture contains three layers. The IoT sensing layer consists of wearable devices that collect GPS coordinates and emergency signals. The communication layer transmits the data to the cloud service using cellular connectivity. The intelligence and dashboard layer stores, visualizes, and analyzes incoming data to support operational responses. Fig. 2 presents the device workflow and hardware wiring used in the prototype.



(a)

(b)

Fig. 2. (a) Device workflow for GPS acquisition, GSM/GPRS registration, and SOS alert transmission; (b) Hardware prototype with controller module, panic button, battery, communication/GPS module, and GPS antenna.

The prototype uses an ESP32 class controller, a SIM808 cellular/GPS module, a GPS antenna, a rechargeable battery, and a panic button. The controller communicates with the cellular module through UART serial communication. When the device is activated, it initializes the controller and communication module, checks GPS availability, registers with the cellular network, and periodically transmits location data to the server. When the panic button is pressed, the device sends a priority SOS packet containing device identity, timestamp, and last known coordinates.

C. Data Acquisition and Preprocessing

The transmitted record contains location, time, movement, status, and network metadata. Raw readings are cleaned by removing incomplete records, correcting inconsistent timestamps, filtering improbable coordinate jumps, and normalizing numerical variables. Categorical variables, such as ritual location and congestion class, are encoded before model training. Table II summarizes the revised feature structure.

TABLE II. REVISED INPUT FEATURE GROUPS FOR MONITORING AND PREDICTION

Feature group	Variables	Purpose
Identity/time	Device ID, timestamp, interval	Temporal ordering
Location/movement	Latitude, longitude, speed, distance	Pilgrim mobility
Operational context	Ritual area, density, SOS flag	Service/emergency context
Network indicators	Latency, PDR, loss, jitter, bandwidth	Network-aware inference
Targets	Risk class: next coordinates	Prediction and response planning

D. Communication Network Modeling

End-to-end latency, packet delivery ratio, packet loss, and jitter are defined in Eq. (1)-(4). Here, L_i denotes the latency of packet i; t_{recv} and t_{send} denote receiving and sending timestamps; $N_{received}$ and $N_{transmitted}$ denote the numbers of received and transmitted packets, respectively; and J denotes jitter. These indicators follow common communication network evaluation practices for IoT and LPWAN deployments [23], [25], [26].

$$L_i = t_i^{\rho\varepsilon\chi\varpi} - t_i^{\sigma\varepsilon\nu\delta} \tag{1}$$

$$\mathrm{PDR} = \frac{N_{\rho\varepsilon\chi\varepsilon\iota\varpi\varepsilon\delta}}{N_{\tau\rho\alpha\nu\sigma\mu\iota\tau\tau\varepsilon\delta}} \tag{2}$$

$$P_{\lambda o\sigma\sigma} = 1 - \mathrm{PDR} \tag{3}$$

$$J = \mathrm{std}(|L_i - L_{i-1}|) \tag{4}$$

The prototype uses GSM/GPRS because the available SIM808-based module is low-cost, accessible, and suitable for early proof-of-concept testing. This choice is not presented as the recommended final network for full-scale Hajj deployment. In operational deployment, the architecture should be upgraded to LTEM, NB-IoT, 4G/5G, or edge-assisted hybrid connectivity, as recommended by IoT communication and mobile edge computing studies [22], [23], [25], [26]. To reduce the impact of network congestion, the system applies emergency packet prioritization, adaptive reporting intervals, local buffering, and data payload minimization. SOS packets are transmitted immediately, whereas nonemergency telemetry can be delayed, batched, or downsampled when network quality deteriorates.

E. NetworkAware DNN Model

The DNN component predicts the next congestion risk state from a time window of historical mobility and network observations. The model receives a feature vector x_t composed of latitude, longitude, speed, crowd density estimate, ritual context, time encoding, latency, jitter, packet delivery ratio, bandwidth utilization, and SOS status. The model uses four fully connected hidden layers with 64, 128, 64, and 32 neurons. Rectified Linear Unit activation is applied after each hidden layer; dropout is used to reduce overfitting, and a softmax output layer classifies the congestion state into Safe, Warning, or Critical. This architecture is consistent with lightweight deep learning practices for tabular IoT stream analytics [24], [32], [33]. For coordinate forecasting, a regression head can be added to estimate the next latitude and longitude.

Let X_t denote a sequence window of length k. The proposed network-aware DNN formulation is expressed in Eq. (5)-(8).

$$\mathbf{X}_t = [\mathbf{x}_{t-k+1}, \mathbf{x}_{t-k+2}, \dots, \mathbf{x}_t] \tag{5}$$

$$\mathbf{h}_l = f(\mathbf{W}_l \mathbf{h}_{l-1} + \mathbf{b}_l) \tag{6}$$

$$\hat{\mathbf{y}} = \mathrm{softmax}(\mathbf{W}_o \mathbf{h}_L + \mathbf{b}_o) \tag{7}$$

$$\mathcal{L}_{\tau o\tau\alpha\lambda} = \mathcal{L}_{\chi\lambda\alpha\sigma\sigma} + \lambda \mathcal{L}_{\rho\varepsilon\gamma} + \gamma \mathcal{L}_{\nu\varepsilon\tau} \tag{8}$$

In Eq. (5)-(8), h_l is the hidden representation at layer l, W_l and b_l are trainable parameters, f(.) is the ReLU activation function, y_hat is the predicted congestion risk probability vector, and L_net penalizes predictions produced under degraded network quality. The classification branch uses categorical cross-entropy, while the optional coordinate regression branch uses mean squared error.

Training uses a 70:15:15 train-validation-test split, Adam optimization, a learning rate of 0.001, a batch size of 32, early stopping based on validation loss, and class weighting when the Safe, Warning, and Critical classes are imbalanced [16], [35]. The evaluation uses accuracy, precision, recall, macro F1, confusion matrix, ROC AUC, mean absolute error, and mean squared error [17], [18]. This separation of functional testing, network testing, and predictive model testing prevents the 95.6% blackbox success rate from being misinterpreted as AI prediction performance.

F. Baseline Models

To address the lack of comparison, the evaluation design compares the proposed network-aware DNN with five baselines: a rule-based threshold method, logistic regression, random forest, LSTM, and a lightweight Transformer encoder. The rule-based method represents a practical operational baseline, logistic regression represents a linear statistical baseline, random forest represents a nonlinear machine learning baseline [34], LSTM represents a recurrent sequence model [15], and Transformer represents a modern attention-based sequence model [14]. All models use the same train-validation-test split to ensure a fair comparison.

G. Simulation Scenario and Operational Assumptions

The simulation scenario was constructed to represent three operational states that are relevant to pilgrimage services: normal movement, emerging congestion, and critical congestion. Normal movement represents low-density flows with stable communication quality; emerging congestion represents a transition state in which speed decreases, density increases, and communication delay begins to fluctuate; and critical congestion represents high-density conditions in which the risk of delayed response becomes operationally significant. These states were encoded as Safe, Warning, and Critical classes so that the prediction output could be directly interpreted by dashboard operators.

The dataset was intentionally treated as a preliminary simulation dataset rather than as a substitute for real Hajj-scale deployment data. Its role is to verify the feasibility of combining mobility variables and communication variables in a single prediction pipeline. Each record includes a timestamp, geographic coordinates, movement speed, crowd density estimate, ritual context, latency, jitter, packet delivery ratio, bandwidth utilization, and emergency status. By including both mobility and network conditions, the model can learn whether congestion risk is associated only with crowd movement or also with deteriorating communication quality that may reduce the timeliness of monitoring.

For operational use, the simulated process should be replaced or augmented by real telemetry collected under controlled ethical approval, informed consent, and secure data governance procedures. Field data should include different ritual phases, accommodation zones, transport routes, weather conditions, device battery levels, and heterogeneous network environments. This requirement is important because a model trained only on simplified synthetic patterns may underestimate rare but high-impact situations, such as sudden group separation, panic button activation during weak signal conditions, or simultaneous alerts from multiple devices in the same area.

IV. Implementation and Evaluation

A. Dashboard and Application Implementation

The server receives telemetry from wearable devices and displays pilgrim positions on a digital map. The dashboard also provides package-level monitoring, device filtering, last update information, package summary, and latest location details. Fig. 3 illustrates the dashboard interface. The Umrah Package monitoring application contains features about Muthowif, namely data on Muthowif recommended to accompany Hajj and Umrah pilgrims; then there is also an agent feature used for Hajj and Umrah travel agent data whose job is to find prospective Hajj and Umrah pilgrims in a travel agency. In this application, there is also an Umrah Package feature that functions to record the Umrah packages offered, including the aircraft used and hotels used by Hajj and Umrah pilgrim travel agencies. Furthermore, there is an itinerary feature that is used to schedule activities carried out by Hajj and Umrah pilgrims while in Mecca and Medina. Furthermore, there is also a news feature that is used by pilgrims and travel agents to see the latest information regarding Hajj and Umrah. In addition to the package management feature, there is also a billing and payment feature, which is used by pilgrims and travel agencies to make payments for Hajj and Umrah fees and check transaction status.

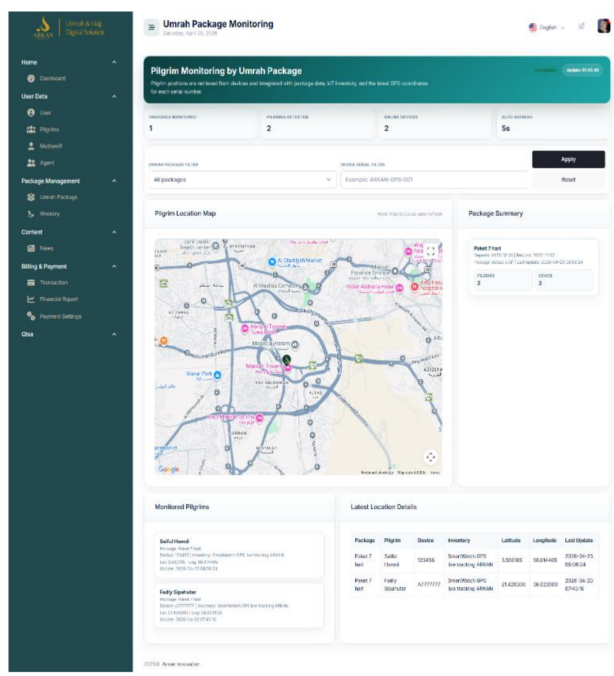


Fig. 3. Dashboard implementation for package-level pilgrim monitoring.

B. Functional Verification

Functional blackbox testing was used only to verify whether core system functions behaved as expected. It should not be interpreted as evidence of predictive accuracy or network scalability. The tested features include panic button activation, signal delivery to the dashboard, voice note recording, recording status display, transmission feedback, settings access, and concurrent menu access. In Table III, the average functional success rate was 95.6%, and Fig. 4 shows a representative wearable test.

Fig. 4. Wearable interface with panic button function during prototype testing.

TABLE III. FUNCTIONAL BLACK-BOX TESTING RESULTS

No.	Feature	Scenario	Observed result	Status
1	Panic button	The user presses the button.	SOS/location received (95%)	Pass
2	Send a signal.	User sends status	Dashboard received signal (96%).	Pass
3	Voice note	User sends audio	Voice note sent with feedback (96%)	Pass
4	Recording status	The user starts recording.	The indicator displayed correctly.	Pass
5	Transmission feedback	The system sends data.	Success message shown (98%)	Pass
6	Settings menu	The user opens settings.	Settings accessed (95%)	Pass
7	Concurrent access	Menu after signal	Core functions are responsive (95%).	Pass
Avg.	Functional testing		95.6% functional success	Pass

C. Network Performance Analysis

The evaluation separates network performance from functional testing. Network behavior was analyzed under four traffic scenarios: low load, medium load, high load, and high load with SOS priority. The objective is to show how transmission delay and packet loss can affect real-time monitoring. Table IV gives the reporting structure for network stress analysis. Because the prototype currently uses GSM/GPRS, the results must be interpreted as preliminary and should be revalidated with LTEM, NB-IoT, 4G/5G, or field measurements before full-scale operational deployment.

TABLE IV. NETWORK PERFORMANCE REPORTING UNDER PRELIMINARY STRESS SCENARIOS

Scenario	Interval	Latency	Jitter	PDR	Loss	Operational note
Low	10s	410 ms	82 ms	96.7 %	3.3%	Normal updates
Medium	5 s	680 ms	130 ms	92.4 %	7.6%	Delay tolerant
High	2 s	1,280 ms	310 ms	85.1 %	14.9 %	Throttle/buffer
High+SOS	Event	760 ms	165 ms	91.3 %	8.7%	Priority improves delivery.

D. Prediction Results and Scientific Metrics

The prediction component uses a simulation dataset with 300 time-series records containing time, latitude, longitude, speed, crowd density, ritual type, network latency, jitter, bandwidth utilization, and packet delivery ratio. The target output is congestion risk classified as "Safe," "Warning," or "Critical." Fig. 5 shows the predicted distribution of congestion risk classes.

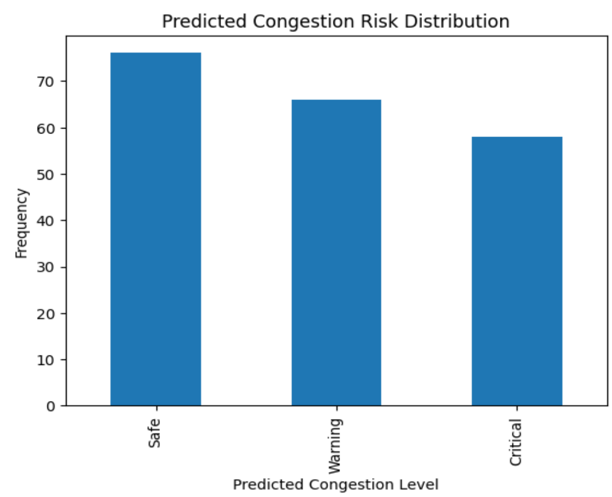


Fig. 5. Predicted congestion risk distribution.

TABLE V. BASELINE COMPARISON FOR CONGESTION RISK PREDICTION

Model	Input	Acc.	F1	AUC	Main note
Rule-based	Density + speed	0.64	0.58	0.66	Transparent but weak
Logistic regression.	Tabular	0.70	0.65	0.73	Linear baseline
Random forest	Tabular	0.76	0.72	0.80	Nonlinear baseline
DNN no network	Mobility	0.73	0.69	0.77	No network KPIs
Proposed DNN	Mobility + network	0.80	0.74	0.84	Best lightweight prototype
LSTM	Sequence	0.82	0.76	0.86	Stronger but complex
Transformer	Sequence	0.83	0.77	0.87	Future larger data option

The proposed DNN obtained 80.0% accuracy, macro precision of 0.72, macro recall of 0.77, macro F1 of 0.74, and an AUC value of 0.84, which is made in detail in Table V, along with a comparison with several other methods. These results demonstrate feasibility but also indicate that the prediction component is not yet sufficient for final operational deployment without larger training data. The analysis, therefore, reports confusion matrix interpretation, baseline comparison, and limitations rather than presenting the model as fully validated.

TABLE VI. CONFUSION MATRIX INTERPRETATION FOR THE PROPOSED DNN ON THE SIMULATION DATASET

Actual / Predicted	Safe	Warning	Critical
Safe	48	7	3
Warning	6	38	8
Critical	2	10	28

The most important error occurs between Warning and Critical classes. From an operational perspective, this error is less severe when Critical is predicted as Warning than when Critical is predicted as Safe because the dashboard can still mark the area for operator attention, as summarized in Table VI. Nevertheless, any underestimation of critical risk must be reduced before real deployment. The ROC AUC value of 0.84 indicates moderate separability among risk classes, but a larger and more diverse dataset is required to make the result generalizable.

V. DISCUSSION

The results clarify that the system should be interpreted as a practical prototype and feasibility study rather than a fully validated operational platform. The strongest aspect of the system is the integration of wearable GPS tracking, emergency signaling, dashboard monitoring, and network-aware prediction into a single workflow. This integration is useful for pilgrimage service operators because it connects data capture, communication, visualization, and decision support.

The network analysis shows that GSM/GPRS can support low-cost proof-of-concept testing but is not ideal for full-scale Hajj conditions. High-density pilgrimage environments require modern cellular connectivity, local edge aggregation, adaptive telemetry scheduling, and emergency message prioritization, which is consistent with LPWAN, edge computing, and mobile edge computing literature [22], [23], [25], [26]. Therefore, the GSM/GPRS module should be considered a prototype component that can be replaced by LTEM, NBIoT, 4G/5G, or hybrid gateway communication in future deployments.

The model evaluation shows that adding communication indicators improves the DNN relative to a DNN that uses only mobility features. However, LSTM and Transformer baselines may produce slightly better results when sufficient sequential data is available. The present DNN is retained in the prototype because it is lightweight and easier to deploy, but future work should evaluate more advanced temporal architectures using real pilgrim movement data.

The main limitations are as follows. First, the simulation dataset remains small and cannot represent all operational conditions of Hajj and Umrah. Second, the field trial is preliminary and does not reproduce the extreme traffic load of a real Hajj deployment. Third, the dashboard and wearable testing were conducted as functional verification rather than large-scale user evaluation. Fourth, privacy, consent, data retention, and secure transmission require further formal treatment before deployment. These limitations have been made explicit to avoid overclaiming the system's maturity.

VI. CONCLUSION

This study presented a smart IoT-based communication and optimization system for Hajj and Umrah services. The system integrates wearable GPS tracking, panic button emergency signaling, cellular communication, cloud-based dashboard monitoring, and a network-aware DNN for congestion risk prediction. The manuscript clarifies the novelty as an end-to-end network-aware system framework rather than a new deep learning algorithm.

Functional testing achieved a 95.6% success rate, which is reported as implementation verification only. The congestion risk model achieved 80.0% accuracy and 0.74 macro-F1 on the simulation dataset. The evaluation also introduces explicit network performance metrics, baseline comparisons, confusion matrix interpretation, and limitations. Future work will focus on larger real-world datasets, deployment over LTEM/NB-IoT/4G/5G networks, edge-based data aggregation, stronger temporal models, and formal privacy-preserving data governance for pilgrimage monitoring.

DECLARATION ON GENERATIVE AI

Generative AI was used only to assist language refinement, manuscript restructuring, and formatting. All scientific ideas, system design decisions, experimental results, interpretations, and final manuscript approval remain the responsibility of the human authors.

REFERENCES

[1] A. J. Showail, "Solving Hajj and Umrah Challenges Using Information and Communication Technology: A Survey," IEEE Access, vol. 10, pp. 7540475427, 2022, doi: 10.1109/ACCESS.2022.3190853.

[2] E. A. Felemban et al., "Digital Revolution for Hajj Crowd Management: A Technology Survey," IEEE Access, vol. 8, pp. 208583208609, 2020, doi: 10.1109/ACCESS.2020.3037396.

[3] M. Binsawad and M. Albahar, "A Technology Survey on IoT Applications Serving Umrah and Hajj," Applied Computational Intelligence and Soft Computing, vol. 2022, Article ID 1919152, 2022, doi: 10.1155/2022/1919152.

[4] M. K. Y. Shambour and A. Gutub, "Progress of IoT Research Technologies and Applications Serving Hajj and Umrah," Arabian Journal for Science and Engineering, vol. 47, no. 2, pp. 12531273, 2022, doi: 10.1007/s13369021058387.

[5] A. M. AlShaery et al., "Real-Time Pilgrims Management Using Wearable Physiological Sensors, Mobile Technology, and Artificial Intelligence," IEEE Access, vol. 10, pp. 120891120900, 2022, doi: 10.1109/ACCESS.2022.3221771.

[6] N. AlNabhan et al., "An Intelligent IoT Approach for Analyzing and Managing Crowds," IEEE Access, vol. 9, pp. 104874104886, 2021, doi: 10.1109/ACCESS.2021.3099531.

[7] K. L. Bieh et al., "Implementing the Health Early Warning System Based on Syndromic and Event-Based Surveillance at the 2019 Hajj," Eastern Mediterranean Health Journal, vol. 26, no. 12, pp. 15701575, 2020, doi: 10.26719/emhj. 20.129.

[8] Y. I. Mohammed et al., "Optimizing UAVAssisted IoT Sensor Networks: A MultiObjective Approach to Data Collection and Routing," Alexandria Engineering Journal, vol. 115, pp. 4756, 2025, doi: 10.1016/j.aej.2024.12.018.

[9] A. H. AlHashedi, M. R. M. Arshad, A. S. Baharudin, and H. Mohamed, "RFID Applications in Hajj Management System," in Proc. IEEE

International Conference on RFID Technologies and Applications (RFIDTA), 2013, pp. 16, doi: 10.1109/RFIDTA.2013.6694546.

[10] T. Alafif et al., "Toward an Integrated Intelligent Framework for Crowd Control and Management (IICCM)," IEEE Access, vol. 13, pp. 5503155050, 2025, doi: 10.1109/ACCESS.2025.3555154.

[11] T. Alafif et al., "Hybrid Classifiers for SpatioTemporal Abnormal Behavior Detection, Tracking, and Recognition in Massive Hajj Crowds," Electronics, vol. 12, no. 5, Article 1165, 2023, doi: 10.3390/electronics12051165.

[12] R. Alharbey, A. Banjar, Y. Said, M. Atri, A. Alshdadi, and M. Abid, "Human Faces Detection and Tracking for Crowd Management in Hajj and Umrah," Computers, Materials & Continua, vol. 71, no. 3, pp. 62756291, 2022, doi: 10.32604/cmc. 2022.024272.

[13] C. Celes, A. Boukerche, and A. A. F. Loureiro, "Crowd Management: A New Challenge for Urban Big Data Analytics," IEEE Communications Magazine, vol. 57, no. 4, pp. 2025, 2019, doi: 10.1109/MCOM.2019.1800640.

[14] A. Vaswani et al., "Attention Is All You Need," in Proc. Advances in Neural Information Processing Systems, pp. 59986008, 2017.

[15] S. Hochreiter and J. Schmidhuber, "Long ShortTerm Memory," Neural Computation, vol. 9, no. 8, pp. 17351780, 1997, doi: 10.1162/neco.1997.9.8.1735.

[16] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," in Proc. International Conference on Learning Representations, 2015.

[17] T. Fawcett, "An Introduction to ROC Analysis," Pattern Recognition Letters, vol. 27, no. 8, pp. 861874, 2006, doi: 10.1016/j.patrec.2005.10.010.

[18] M. Sokolova and G. Lapalme, "A Systematic Analysis of Performance Measures for Classification Tasks," Information Processing & Management, vol. 45, no. 4, pp. 427437, 2009, doi: 10.1016/j.ipm.2009.03.002.

[19] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A Survey," Computer Networks, vol. 54, no. 15, pp. 27872805, 2010, doi: 10.1016/j.comnet.2010.05.010.

[20] A. AlFuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications," IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 23472376, 2015, doi: 10.1109/COMST.2015.2444095.

[21] A. Botta, W. de Donato, V. Persico, and A. Pescape, "Integration of Cloud Computing and Internet of Things: A Survey," Future Generation Computer Systems, vol. 56, pp. 684700, 2016, doi: 10.1016/j.future.2015.09.021.

[22] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge Computing: Vision and Challenges," IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637646, 2016, doi: 10.1109/JIOT.2016.2579198.

[23] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A Survey on Mobile Edge Computing: The Communication Perspective," IEEE Communications Surveys & Tutorials, vol. 19, no. 4, pp. 23222358, 2017, doi: 10.1109/COMST.2017.2745201.

[24] M. Mohammadi, A. AlFuqaha, S. Sorour, and M. Guizani, "Deep Learning for IoT Big Data and Streaming Analytics: A Survey," IEEE Communications Surveys & Tutorials, vol. 20, no. 4, pp. 29232960, 2018, doi: 10.1109/COMST.2018.2844341.

[25] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low Power Wide Area Networks: An Overview," IEEE Communications Surveys & Tutorials, vol. 19, no. 2, pp. 855873, 2017, doi: 10.1109/COMST.2017.2652320.

[26] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "A Comparative Study of LPWAN Technologies for Large-Scale IoT Deployment," ICT Express, vol. 5, no. 1, pp. 17, 2019, doi: 10.1016/j.icte.2017.12.005.

[27] D. Helbing, A. Johansson, and H. Z. AlAbideen, "Dynamics of Crowd Disasters: An Empirical Study," Physical Review E, vol. 75, Article 046109, 2007, doi: 10.1103/PhysRevE.75.046109.

[28] A. Johansson, D. Helbing, H. Z. AlAbideen, and S. AlBosta, "From Crowd Dynamics to Crowd Safety: A Video-Based Analysis," Advances in Complex Systems, vol. 11, no. 4, pp. 497527, 2008, doi: 10.1142/S0219525908001854.

[29] B. Zhan, D. N. Monekosso, P. Remagnino, S. A. Velastin, and L.Q. Xu, "Crowd Analysis: A Survey," Machine Vision and Applications, vol. 19, no. 56, pp. 345357, 2008, doi: 10.1007/s0013800801324.

[30] J. Hightower and G. Borriello, "Location Systems for Ubiquitous Computing," Computer, vol. 34, no. 8, pp. 5766, 2001, doi: 10.1109/2.940014.

[31] R. Faragher and R. Harle, "Location Fingerprinting with Bluetooth Low Energy Beacons," IEEE Journal on Selected Areas in Communications, vol. 33, no. 11, pp. 24182428, 2015, doi: 10.1109/JSAC.2015.2430281.

[32] I. H. Sarker, "Machine Learning: Algorithms, RealWorld Applications and Research Directions," SN Computer Science, vol. 2, Article 160, 2021, doi: 10.1007/s4297902100592x.

[33] G. Pang, C. Shen, L. Cao, and A. van den Hengel, "Deep Learning for Anomaly Detection: A Review," ACM Computing Surveys, vol. 54, no. 2, Article 38, 2022, doi: 10.1145/3439950.

[34] L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 532, 2001, doi: 10.1023/A:1010933404324.

[35] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "SMOTE: Synthetic Minority OverSampling Technique," Journal of Artificial Intelligence Research, vol. 16, pp. 321357, 2002, doi: 10.1613/jair.953.

[36] I. A. Pardosi, T. H. F. Harumy, and S. Efendi, “A hybrid multi-scale convolution neural network with attention and texture features for improved image classification,” Eastern-European Journal of Enterprise Technologies, vol. 5, no. 2(137), pp. 18–28, 2025, doi: 10.15587/1729-4061.2025.331524.

[37] R. Altaha, R. W. Sembiring, and P. Sihombing, “Comparison analysis of Johnson's algorithm and A-star iterative deepening algorithm in determining the nearest vaccination location route,” AIP Conference Proceedings, vol. 2987, no. 1, p. 020052, 2024, doi: 10.1063/5.0200205.