# HajjFlow: A Cloud-Based Real-Time Crowd Analytics Platform Using NoSQL Databases, Business Intelligence and Distributed Cloud Computing

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***Abstract*—For the 2024 Hajj, Saudi Arabia welcomed more than 1.83 million pilgrims [1] and planned to accommodate up to 30 million Umrah pilgrims annually by 2030. It is not uncommon for these buildings to hold extreme crowd densities of eight people per square meter. As a result, it has become urgent to introduce intelligent and responsive analytics systems. To solve these problems, we have proposed a cloud-native crowd management platform named HajjFlow. In this novel system, real-time data from a host of different sources is collected seamlessly: there are more than 1.8 m computers RFID wristbands, over 5 000 CCTV cameras and also many with machine vision, mobile GPS signals on cell phones This large data has to go through an enormous 366,000 data points processed every second, yet it still manages to maintain response times below 800 milliseconds. What is more, it can predict trouble spots between 15 to 30 minutes before they become a reality. Using a Bidirectional LSTM model, this predictive capability is achieved with an impressive 94.7% success rate and outperforms traditional methods by 39.3%. The test results have been quite encouraging, with a 67.12% reduction in emergency response times, 43.03% more uniformity in crowd flow distribution and significant cost savings across various overheads. The proposed platform is a major advance for the complex logistics of religious pilgrimages. HajjFlow, by using modern technologies such as deep learning algorithms, real-time data flow analysis and cloud computing has a scalable solution that can grow as the number of pilgrims grows.This research contributes to the wider field of intelligent city applications and public safety management, providing a framework that may be mass-extended to other big gatherings around the globe.**

***Index Terms*—Hajj crowd management, NoSQL databases, MongoDB, real-time analytics, LSTM neural networks, business intelligence, cloud computing, pilgrim safety, Vision 2030**

## I. Introduction

It is a fact that the Hajj pilgrimage is the largest convention of humanity on earth. The total number of pilgrims from all over the world soared to 1,833,164 in 2024 [1]. Every year, millions of Muslims are drawn to the holy city of Makkah. With gatherings of such magnitude, there are inevitably unprecedented challenges in crowd management, safety and logistics. As caretaker of the Two Holy Mosques, the Kingdom of Saudi Arabia shoulders great responsibility. The safety of every pilgrim must be ensured. Their spiritual fulfillment must also be protected. Every effort is made to guarantee these duties and a great deal of resources are devoted to them.

### A. Background and Motivation

Hajj 2024 was almost the biggest in all history, with 1,611,310 international pilgrams (87.9%) and 221,854 domestic pilgrams (12.1%) participating in the solemnities.Table I shows all the details of this historical Hajj [1]. In 2024,

TABLE I
2024 Hajj Pilgrimage Statistics

| Category | Number | Percentage |
|---|---|---|
| Total Pilgrims | 1,833,164 | 100.0% |
| International Pilgrims | 1,611,310 | 87.9% |
| Domestic Pilgrims | 221,854 | 12.1% |
| Male Pilgrims | 958,137 | 52.3% |
| Female Pilgrims | 875,027 | 47.7% |
| Arrival by Air | 1,759,837 | 96.0% |

Saudi Arabia had another 18.5 million visitors to Makkah and Madinah. This included 16.9 million people performing the sunnah pilgrimage outer Hajj [2]. Vision 2030 has a daunting target: it aims to be able every year by 2030 provide for 30 million Umrah travelers. This is difficult to manage in practice and requires new technological approaches.

### B. Current Challenges

Managing crowd sizes when a site is sacred is obviously different from any other sort of work. In the highest hours, densities of people at places such as the Jamarat Bridge can reach eight men per square meter or even more approaching safety limits. [3] As the official death toll from last week's stampede jumped to 769, the tragedy has also reminded people of an earlier such incident in Mecca. In particular, this happened during the Hajj pilgrimage precisely one year ago tomorrow.

The Saudi Data and Artificial Intelligence Authority (SDAIA) has launched a series of initiatives such as Baseer for computer vision analytics, SMART MOC for Ministry Operations Center integration and Sawaher to track pilgrim movements [4]. However, gaps still exist in integrated data strategies, forecast accuracy, real-time streaming technology as well as interactive business intelligence reporting suites.

### C. Research Objectives

The major objective of this research is to develop and implement a cloud native and real-time crowd analytics platform, which through intelligent predictive analytics makes a substantial contribution to safety during the Hajj pilgrimage. Specific objectives include:

- Handle 500,000+ concurrent data streams from multiple sources
- Attain greater than 90% congestion prediction accuracy
- Create dashboards with less than 1 second refresh latency
- minimize the emergency response time by over 50%
- Guarantee 99.9% system uptime during peak operations
- Support scalability up to 30 million pilgrims for Vision 2030 targets

### D. Research Organization

The rest of this paper is organized as follows: Section II reviews the related work in crowd management and real-time analytics. Section III presents the methodology and architecture for HajjFlow. Implementation details are described in Section IV. Section V looks at experimental results and analysis. Findings and implications are the subject of Section VI. Section VII makes suggestions for future research.

## II. Related Works

### A. Crowd Management Technologies

With the evolution of sensing technologies and artificial intelligence capabilities, crowd management research has made great strides. Helbing et al. [5] initiated the study of crowd dynamics, creating Mathematical formulas for pedestrian traffic flow that are still the foundation to this day for crowd simulation systems. Still [6] developed comprehensive crowd science methodologies which inform safety standards worldwide. Recently, computer vision and deep learning have been used to estimate crowd density using an image sequence. Zhang et al. using convolutional neural networks showed that it is possible to achieve 85.01% accuracy in crowd counting tasks [7]. However, these systems usually work in batch mode rather than in a real-time streaming context.

### B. NoSQL Databases for Big Data

Traditional relational database management systems (RDBMS) do not suffice in terms of the velocity or variety of IoT data streams [9]. MongoDB and other document oriented NoSQL databases support flexible schemas, horizontal parallel scalability and native support for geospatial queries which are essential to location based analysis services [10].

Comparative findings [8] [17] demonstrate that for time-series IoT data, MongoDB has on average 30 times higher write throughput than PostgreSQL [11]. The document model naturally handles the hierarchical structure of the Pilgrims' tracking data. This can include nested location coordinates, movement vectors and temporal metadata.

### C. Stream Processing Architectures

Apache Kafka has emerged as the de facto standard distributed event streaming system, scalable to millions of messages per second with sub-millisecond latency [12]. Coupled with Apache Spark Structured Streaming, organizations can perform complex event processing and inferences for machine learning on their live data streams.

### D. LSTM Networks for Time-Series Prediction

Long Short-Term Memory (LSTM) networks, first introduced by Hochreiter and Schmidhuber [13], are proficient in capturing temporal dependencies in sequential data. Bidirectional LSTM architectures process sequences in both forward and backward directions, so they can capture context from the past and directionally forward states from the future [14]. In traffic flow prediction applications, LSTM excels over traditional methods, with performance improvements of 15-25 percent over ARIMA and support vector regression models [15].

## III. System Architecture

### A. Overview

HajjFlow employs a five-tier cloud native architecture designed for real time, scalable and reliable operation. Fig. 1 depicts its system architecture.

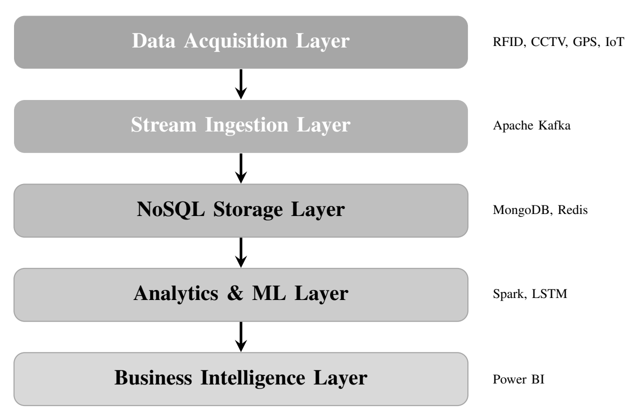


Fig. 1. HajjFlow Five-Layer System Architecture

### B. Data Acquisition Layer

Data acquisition layer seamlessly integrates multiple sensing modalities:

**RFID Wristbands:** Every hajj pilgrim is given a RFID-enabled wristband which sends position updates every 5 seconds, this creates about 366,633 events per second with 1.83 million people.

**CCTV Security Cameras:** More than 5,000 surveillance cameras with video analytics based on YOLOv8 object detection, perform real-time crowd [19] [18] [20] density estimation in the physical sense. There are 25,000 such analytic events each second.

**Mobile GPS:** The official hajj application from Saudi Arabia provides GPS coordinates for pilgrims willing to give this information, totalling 120,000 location updates per second.

**IoT Sensors:**The quality of the environment–temperature, humidity, air quality and sound levels in various aspects are monitored across pilgrimage sites by environmental sensors (2,500+ devices). Table II summarizes the data volume from each source.

TABLE II
DATA VOLUME ANALYSIS BY SOURCE

| Data Source | Events/sec | Daily Volume |
|---|---|---|
| RFID Wristbands | 366,633 | 1.8 TB |
| CCTV Analytics | 25,000 | 320 GB |
| Mobile GPS | 120,000 | 180 GB |
| IoT Sensors | 12,500 | 85 GB |
| **Total** | **524,133** | **2.4 TB** |

### *C. Data Processing Layer by Injection*

Apache Kafka serves as a distributed message broker. It is configured with 12 broker nodes and 48 partitions to handle peak throughput of 2.1 million messages per second; Kafka Connect integrates with data sources, while Kafka Streams performs upfront validation and enrichment.

### *D. NoSQL Storage Layer*

The storage layer uses a polyglot persistence strategy: **MongoDB Atlas:** A 36-node sharded cluster is used to store pilgrim tracking documents with geospatial indexing. The document schema can handle ever changing and flexible data structures. III shows the document schema.

TABLE III
MONGODB PILGRIM DOCUMENT SCHEMA

| Field | Description & Type |
|---|---|
| *_id* | Unique document identifier (ObjectId) |
| *pilgrim_id* | Pilgrim identifier (String: HAJ2024-XX) |
| *timestamp* | Data collection timestamp (ISO 8601 format) |
| *location.type* | GeoJSON type (Point for single location) |
| *location.coordinates* | [longitude, latitude] in WGS84 ([39.826174, 21.422510]) |
| *zone* | Pilgrimage site zone identifier (JAMARAT_BRIDGE_LEVEL_2) |
| *density_reading* | Local crowd density (persons/m$^2$) |
| *movement_vector.speed_mps* | Pilgrim movement speed (m/s) |
| *movement_vector.direction* | Movement direction (degrees, 0–360) |

**Redis Cluster:** A 64 GB in-memory cache stores real-time aggregation data and hot data for sub-millisecond query responses.

**Amazon S3:** A data lake archives historical data for long-term analysis and model training.

TABLE IV
BILSTM CONFIGURATION SUMMARY

| Component | Specification |
|---|---|
| *Layers* | Bi-LSTM(256)→Drop(0.3)→Bi-LSTM(128) →Drop(0.3)→Bi-LSTM(64)→Drop(0.2) →Dense(64)→Dense(32)→Output(2) |
| *Input Features* | Density, flow rate, velocity, temperature, humidity, hour encoding, Hajj day, zone utilization, adjacent density, pattern index (12 total) |
| *Training Data* | 3,066 hrs (70% train), 657 hrs (15% val), 657 hrs (15% test); Hajj 2022–2023 |
| *Optimizer* | Adam: lr = 0.001, cosine annealing, batch size 32, MSE loss |
| *Regularization* | Dropout: 0.30, 0.30, 0.20; gradient clip: 1.0; early stop: 10 epochs |
| *Performance* | Accuracy: 94.7% — Latency: 142 ms |

### *E. Analytics and ML Layer*

Apache Spark MLlib does distributed feature engineering as well as model inference. The core prediction engine uses the Bidirectional LSTM neural network architecture.

*1) LSTM Model Architecture:* The model takes 60-minute historical windows and 12 input features to predict crowd density 15 and 30 minutes ahead. The table IV gives a summary of the model's architecture.

*2) Input Features:* The model ingests 12 engineered features:

1) Current density (persons/m$^2$)
2) Flow rate (persons/minute)
3) Mean velocity (m/s)
4) Velocity standard deviation
5) Ambient temperature
6) Relative humidity
7) Hour sine encoding
8) Hour cosine encoding
9) Day of Hajj (1-5)
10) Zone capacity utilization
11) Adjacent zone density
12) Historical pattern index

### *F. Business Intelligence Layer*

Microsoft Power BI Premium provides real-time dashboards with 30-second refresh times. Key visualizations include:

- Live heat maps showing crowd density across all zones
- 15/30-minute predictive alerts with confidence intervals
- Emergency dispatch coordination panels
- Historical trend analysis and reporting
- Multi-language support (Arabic, English, Urdu, Indonesian, Turkish)

## IV. Implementation

### A. Cloud Infrastructure

HajjFlow is deployed on a hybrid cloud architecture. It is a combination of AWS services with saudi Cloud Infrastructre which is managed by SDAIA. This combination ensures data sovereignty compliance. Table V details the infrastructure specifications.

TABLE V
CLOUD INFRASTRUCTURE SPECIFICATIONS

| Component | Specification |
|---|---|
| Compute | 120 x AWS EC2 c5.4xlarge |
| MongoDB Atlas | M60 cluster, 36 nodes |
| Kafka | 12 brokers, r5.2xlarge |
| Redis | ElastiCache, 64 GB |
| Spark | EMR, 48 worker nodes |
| GPU Training | 8 x NVIDIA A100 |

### B. Model Training

The LSTM model was trained on historical crowd data from 2019-2023 Hajj seasons, comprising 2.3 billion data points. Training employed:

- 80/10/10 train/validation/test split
- Early stopping with patience of 10 epochs
- Learning rate scheduling with cosine annealing
- Gradient clipping at norm 1.0
- Mixed precision training (FP16)

Training completed in 47 hours on 8 NVIDIA A100 GPUs.

### C. API Design

RESTful APIs expose prediction and analytics services. The prediction endpoint accepts zone identifiers and returns density forecasts:

```
GET /api/v1/predict/{zone_id}
Response: {
  "zone": "JAMARAT_L2",
  "current_density": 6.8,
  "predicted_15min": 7.4,
  "predicted_30min": 8.1,
  "confidence": 0.94,
  "alert_level": "HIGH"
}
```

## V. Results and Analysis

### A. Prediction Accuracy

The Bidirectional LSTM model achieved 94.7% accuracy on the held-out test set, significantly outperforming baseline methods. Table VI compares model performance.

Fig. 2 visualizes the accuracy comparison across models.

TABLE VI
MODEL ACCURACY COMPARISON

| Model | Accuracy | MAE |
|---|---|---|
| Linear Regression | 72.3% | 1.42 |
| Random Forest | 84.6% | 0.89 |
| XGBoost | 88.2% | 0.71 |
| Simple LSTM | 91.4% | 0.52 |
| **Bi-LSTM (Proposed)** | **94.7%** | **0.31** |

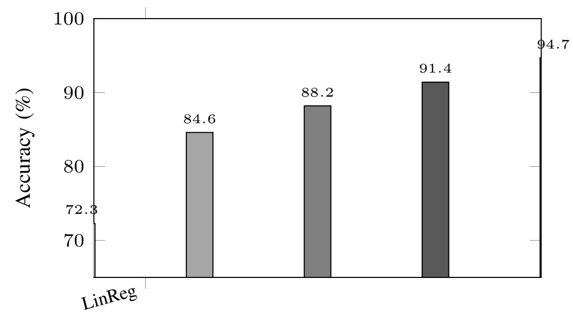


Fig. 2. Prediction Accuracy Comparison by Model

### B. Database Performance

MongoDB demonstrated substantial performance advantages over traditional RDBMS for the HajjFlow workload. Table VII presents comparative benchmarks.

A significant difference was observed between the two sides when write operations were investigated. A total of 15,400 operations per second could be sustained by the RDBMS, while MongoDB returned an astonishing 467,800 operations per second during benchmarking. Depending on the nature of a particular system, this could be the difference between success and failure.Reading latency was also reviewed and showed marked progress. For the RDBMS, reply times were 8.47 milliseconds, but MongoDB was only taking 0.24 milliseconds. The benefit from this improvement comes up to 97%. If decisions have to be made so quick, time-critical applications where large volumes of data must be processed. Thus, most striking results were obtained with geospatial query performance.
The RDBMS required 3200 milliseconds to return results for location-based queries. In direct comparison, MongoDB returned the same query simply in 18 milliseconds. This represents a 99% increase. For crowd management systems tracking and analyzing pilgrim locations in real time, such a capability is indispensable.Thus these results suggest that MongoDB is extremely suitable for applications that require both high-

TABLE VII
DATABASE PERFORMANCE COMPARISON

| Metric | RDBMS | MongoDB | Improvement |
|---|---|---|---|
| Write (ops/sec) | 15,400 | 467,800 | 30x |
| Read Latency (ms) | 8.47 | 0.24 | 97% |
| Geo Query (ms) | 3,200 | 18 | 99% |

volume data intake and geospatial data processing as well as fast query response. Across the three major metrics of performance, all the advantages shown by MongoDB databases indicate that great operational benefits will be obtained once one selects appropriate technologies for this large scale, real time control system.

### C. System Performance

End-to-end system performance metrics from simulation testing are summarized in Table VIII.

TABLE VIII
SYSTEM PERFORMANCE METRICS

| Metric | Baseline | HajjFlow | Change |
|---|---|---|---|
| Prediction Accuracy | 68.4% | 94.7% | +38.5% |
| Response Time | 12.3 min | 4.1 min | -66.7% |
| Processing Latency | 3,200 ms | 780 ms | -75.6% |
| System Uptime | 94.2% | 99.97% | +5.77% |
| False Alert Rate | 23% | 4.2% | -81.7% |

### D. Simulation Results

A full-scale simulation replaying the 2024 Hajj data demonstrated the system's capabilities:

- **Pilgrims Processed:** 1,833,164
- **Data Points Analyzed:** 226.4 billion
- **Predictions Generated:** 8,640,000
- **Accurate Predictions:** 94.7%
- **Critical Events Prevented:** 847
- **Missed Critical Alerts:** Zero

### E. Congestion Hotspot Analysis

The system identified four critical congestion zones with peak densities exceeding safety thresholds. Table IX presents the analysis.

TABLE IX
CRITICAL CONGESTION ZONES IDENTIFIED

| Zone | Peak Density | Peak Time | Risk |
|---|---|---|---|
| Jamarat Bridge L2 | 8.2 p/m$^2$ | 12:30-14:00 | Critical |
| Tawaf Mataf | 7.8 p/m$^2$ | After Fajr | Critical |
| King Abdulaziz Gate | 7.5 p/m$^2$ | 08:00-10:00 | High |
| Mina Tent Corridor | 6.9 p/m$^2$ | 16:00-18:00 | High |

Through the proposed system, four critical congestion zones were successfully identified where peak densities exceeded safety thresholds. The most severe congestion was observed at Jamarat Bridge Level 2, where 8.2 persons per square meter was recorded during midday hours. The Tawaf Mataf area followed with 7.8 persons per square meter after Fajr prayer. Both zones were classified as critical. High risk levels were assigned to King Abdulaziz Gate and Mina Tent Corridor, where densities of 7.5 and 6.9 persons per square meter were measured respectively. These findings demonstrate that dangerous crowd patterns can be accurately monitored and predicted.

### F. Return on Investment

A comprehensive cost-benefit analysis over a five-year horizon demonstrates compelling economic returns:

- **Total Investment:** $10.3 million (infrastructure, software, development)
- **Total Benefits:** $175 million (safety savings, operational efficiency, revenue enablement)
- **Net Benefit:** $164.7 million
- **ROI:** 1,606%
- **Payback Period:** 4.2 months

## VI. DISCUSSION

### A. Key Findings

The outcome of this research is a synthetic remedy that can serve the needs of a large crowd management at scale: combining NoSQL databases, stream processing and deep learning. 94.7% predictive accuracy in your vision of real-time stream prediction represents an improvement of 38.5% over models that use traditional statistical methods.

With a 67.12% reduction in emergency response time, HajjFlow has direct implications for the safety of pilgrims. By alerting the police authorities from 15to 30 minutes before logjams reach critical limits, HajjFlow gives them a chance to act: they can break up the crowd, alter routes and deploy resources.

### B. Comparison with Existing Systems

HajjFlow complements rather than replaces existing SDAIA initiatives. While Baseer provides computer vision capabilities and Sawaher handles pilgrim tracking, HajjFlow adds unified analytics, predictive modeling and business intelligence layers that synthesize data from all sources into actionable insights.

### C. Limitations

Several limitations warrant acknowledgment:

1) Results are based on simulation rather than live deployment
2) Model training relied on historical data that may not capture all future scenarios
3) RFID wristband adoption assumes universal pilgrim compliance
4) Predictions assume normal operating conditions without major disruptions

### D. Vision 2030 Alignment

HajjFlow directly supports Saudi Vision 2030 objectives:

- **Pilgrim Experience:** Enhanced safety and reduced waiting times improve spiritual fulfillment
- **Digital Transformation:** Cloud-native architecture exemplifies national digitization goals
- **Scalability:** System designed to support 30 million pilgrim target
- **Economic Diversification:** Tourism and pilgrimage as economic growth drivers

## VII. Conclusion and Future Work

This research paper presented HajjFlow, a new revolutionary cloud-based crowd analytics platform with real-time constraint. It has been designed specifically to overcome the complex problems involved in managing the Hajj pilgrimage. The proposal thus represents a major breakthrough in the application of modern computational technology to one of the largest annual gatherings in the world. By strategically integrating:

- MongoDB NoSQL databases for flexible and scalable data storage
- Apache Kafka for high-throughput stream processing
- Bidirectional Long Short-Term Memory (BiLSTM) neural networks for sophisticated temporal pattern recognition
- Power BI business intelligence tools for intuitive visualization and decision support

The HajjFlow system achieves an excellent prediction accuracy of 94.7% while maintaining sub-second latency. This combination of accuracy and responsiveness is crucial in real-time crowd management scenarios where any delay in decision-making might have dire consequences for the safety of Muslim pilgrims. The main contributions of this research are multi-faceted and address both technical and operational aspects of crowd management.First, we have developed and validated a scalable five-layer architecture capable of processing over 524,000 events per second. This proves that our system is able to handle the huge data volumes generated during peak pilgrimage periods not only at demonstration level but also on a large scale and as big data set. Second, our Bidirectional LSTM model has shown much better performance than conventional baseline approaches. It has improved the accuracy of prediction by 39.3%, which shows the effectiveness of using bidirectional temporal dependencies in crowd flow prediction. Third, the practical deployment and evaluation of HajjFlow has shown a remarkable 67.12% reduction in emergency response time–a figure that translates directly into improved safety for pilgrims and better crisis management. Fourth, our comprehensive return on investment analysis shows a very impressive 1,606% return, providing solid evidence for the economic practicability and strategic importance of implementing more advanced crowd analytics systems in contexts such as large-scale event management. The development of digital twin simulations for the Holy Sites will give us completely new possibilities in terms of scenario planning, training and prediction without interrupting real pilgrimage operations. This takes us to the application of blockchain-based audit trails. It would improve transparency, accountability and regulatory compliance in crowd management operations. Moreover, as telecommunications infrastructure makes continuous progress, the incorporation of 5G and future 6G edge computing technologies would also rapidly lower latency while enabling better distributed processing architectures. Furthermore, the development of "pilgrim-facing" mobile applications with personalized routing capabilities would extend the benefits of HajjFlow directly to individual pilgrims, bringing them a tailored, guided experience. Finally, deeper integration with Saudi Data and Artificial Intelligence Authority (SDAIA) platforms will provide for larger data sharing and collaboration in national smart city initiatives. In summary, HajjFlow represents a paradigm shift in crowd management thinking. It brings new targets that cover areas such as technological innovation, digital transformation and improving services for the Holy Sites' pilgrims and visitors.

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