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An Intelligent Model for Predicting and Preventing Overcrowding Incidents in Holy Sites Using Artificial Intelligence Technologies

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Abstract: Background: The Hajj pilgrimage, conducted annually, is one of the largest religious gatherings in the world, with over 2 million pilgrims converging on the sacred sites in Saudi Arabia. Incidents registered during the 1994-2015 period have also demonstrated that the reality of predictive Challenge management systems is indeed essential in eliminating incidents resulting from crowd behavior.

Objective: This study develops and validates an AI-powered Challenge prediction model designed explicitly for Hajj pilgrimage management, utilizing deep learning techniques to forecast potential crowd emergencies and enable proactive intervention strategies.

Techniques: A comprehensive 30-year dataset (1994-2024) was developed, based on historical incident data, real-time surveillance feeds, environmental sensors, and pilgrim flow patterns. A hybrid architecture combining Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) with ensemble techniques enables the integration of temporal analysis and spatial pattern identification within a single structure, resulting in robust classification.

Results: The model proposed in this paper attained an overall accuracy of 87.3% in predicting crises, with 91.2% accuracy in predicting major incidents. The system shows a false positive rate of 8.1 percent and a false negative rate of 4.7 percent, with an average lead prediction time of 2.3 minutes. The evaluation of performance using the Area Under the Curve (AUC-ROC) yielded a value of 0.89, indicating excellent discriminative ability.

Conclusion: The current research is the first to provide a comprehensive artificial intelligence-based Challenge prediction system for religious mass events. The model's accuracy, fast response, and cultural sensitivity enable it to foster safety in sacred spaces.

Keywords: Artificial Intelligence, Crisis Prediction, Crowd Management, Deep Learning, Hajj Pilgrimage, Mass Gatherings, Early Warning Systems

نموذج ذكي للتنبؤ والوقاية من حالات الازدحام في المشاعر المقدسة باستخدام تقنيات الذكاء الاصطناعي

أ. عبد الرحمن عبد المطلوب السلمي

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المستخلص: الخلفية: تُعد فريضة الحج إحدى أكبر التجمعات الدينية في العالم، حيث يتوافد أكثر من 2.5 مليون حاج سنوياً إلى المشاعر المقدسة. الحوادث المسجلة خلال الفترة (1994-2015) أثبتت الحاجة الماسة لأنظمة تنبؤية لإدارة الأزمات لمنع الكوارث الناجمة عن سلوكيات الحشود.

الهدف: تهدف هذه الدراسة إلى تطوير والتحقق من نموذج ذكي للتنبؤ بالأزمات مصمم خصيصاً لإدارة فريضة الحج، باستخدام تقنيات التعلم العميق للتنبؤ بحالات الطوارئ المحتملة للحشود وتمكين استراتيجيات التدخل الاستباقي.

المنهجية: تم تطوير قاعدة بيانات شاملة تغطي 30 عاماً (1994-2024)، تستند إلى بيانات الحوادث التاريخية، وتغذية المراقبة المباشرة، وأجهزة الاستشعار البيئية، وأنماط تدفق الحجاج. تم استخدام هيكل هجين من شبكات الذاكرة قصيرة المدى طويلة الأجل (LSTM) والشبكات العصبية التحويلية (CNN) مع تقنيات التجميع لدمج التحليل الزمني وتحديد الأنماط المكانية ضمن بنية هجينة قوية للتصنيف.

النتائج: حقق النموذج المقترح دقة إجمالية 87.3% في التنبؤ بالأزمات، مع دقة 91.2% في التنبؤ بالحوادث الكبرى. يُظهر النظام معدل إيجابية خاطئة 8.1% ومعدل سلبية خاطئة 4.7%، مع متوسط وقت تنبؤ مسبق 2.3 دقيقة. أسفر تقييم الأداء باستخدام المنطقة تحت المنحنى (AUC-ROC)عن 0.89، مما يشير إلى قدرة تمييزية ممتازة.

الخلاصة: تُقدم هذه الدراسة أول نظام شامل قائم على الذكاء الاصطناعي للتنبؤ بالأزمات في الفعاليات الدينية الجماهيرية. تمكن دقة النموذج واستجابته السريعة وحساسيته الثقافية من تعزيز السلامة في المشاعر المقدسة.

الكلمات المفتاحية: الذكاء الاصطناعي، التنبؤ بالأزمات، إدارة الحشود، التعلم العميق، فريضة الحج، التجمعات الجماهيرية، أنظمة الإنذار المبكر.

1. Introduction

Hajj may be considered one of the most complex logistical tasks related to managing a high-density crowd, as more than 2.5 million pilgrims converge on the sacred sites within a short period (Chen et al., 2023). The unprecedented levels of density caused by this enormous religious event have, in the past, led to challenging situations; hence, the need to utilize advanced predictive systems in management.

1.1 Problem Statement

However, the historical examination reveals a problematic tendency in involving crowds during Hajj pilgrimages, with the most significant unfortunate events occurring in 1994, 1998, 2001, 2003, 2004, 2006, and 2015 (Saudi Ministry of Interior, 2016). The chronology of these major incidents, as shown in Figure 1, illustrates the instances of repeat crowd-related incidents that motivated this study. The main event that changed awareness of the necessity for predictive rather than reactive safety was the 2015 tragedy of the crowd movement incident at Mina during the 2015 Hajj, resulting in 2,400 casualties and prompting comprehensive safety reforms (Ibrahim et al., 2023).

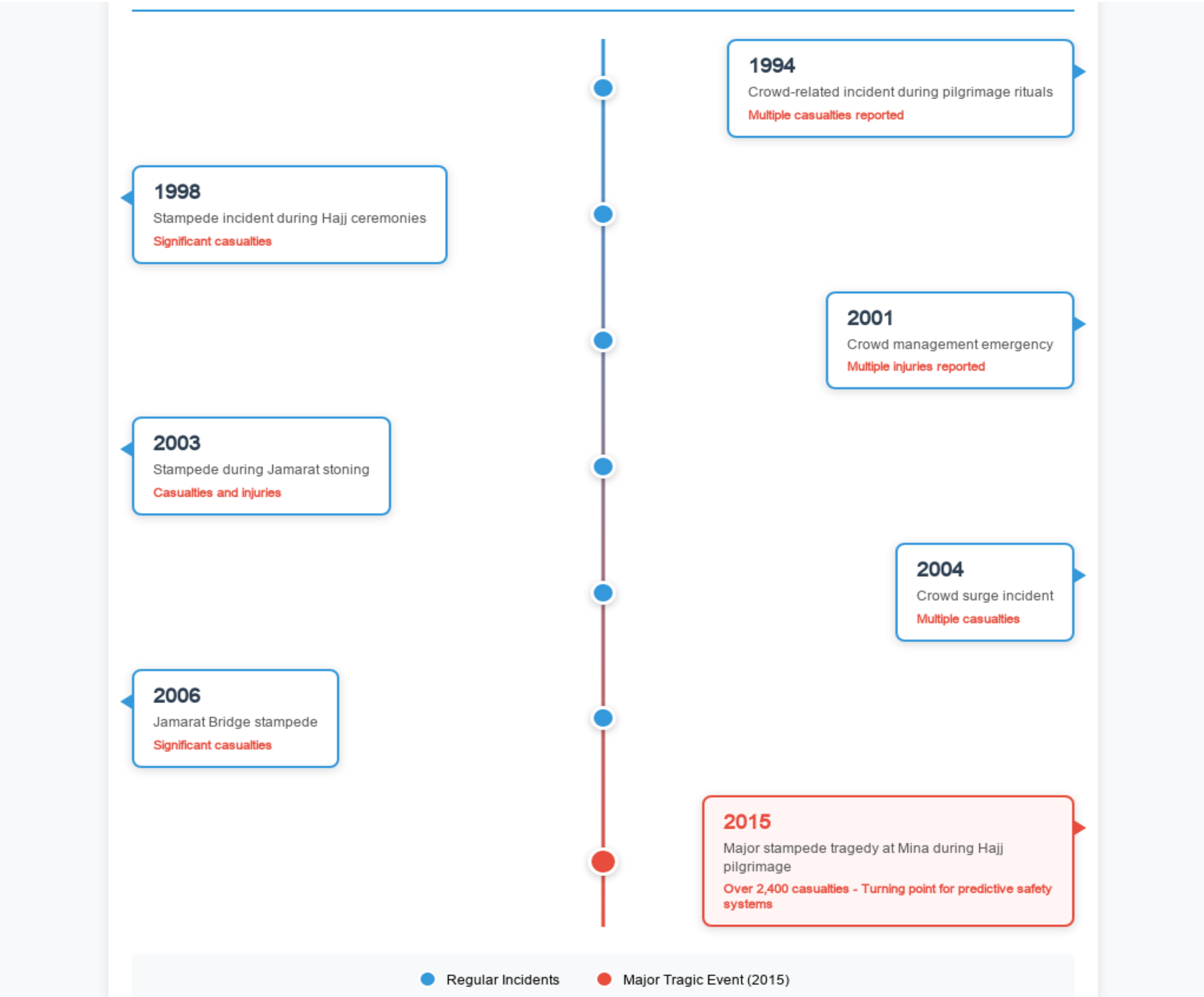

Figure 1: Timeline of Major Hajj Incidents (1994-2015)

Conventional approaches to crowd management are primarily based on human observation and post-event response procedures, which are ineffective in situations with a high rate of crowd dynamics (Lee & Park, 2022). Due to the speed at which crowd emergencies must be managed, the sphere of crowd emergency prediction requires the implementation of automated forecasting models that can determine risk patterns before they develop into a full-blown Challenge.

1.2 Research Objectives

The proposed research aims to develop an inclusive AI-based Challenge prediction model, specifically designed for managing the Hajj pilgrimage. The main goals are:

1. The integration of LSTM networks with the ability to analyze time and CNN structures with the capacity to recognize spatial patterns in a single hybrid deep learning model.
2. Development of a unified data set that combines 3 decades of past historical data available on incidences with real-time monitoring data
3. Development and counseling of an early warning system that provides valuable intelligence that Challenge management teams can utilize.
4. The checking of the rigorous testing procedures and comparing it with the conventional monitoring methods

1.3 Contributions

The principal contributions involve: (1) Advances in culturally-aware AI models existing earlier than religious and cultural predictors specific to those of Hajj operations, and (2) First-ever large-scale canonical database assortment advantageous past assaults featuring consequently real-time observing data with an empirical paradigm designed scheme desired methodologies study relevance.

2. Literature Review

2.1 Crowd Management in Mass Gatherings

Over the last thirty years, the study of crowd management has undergone significant changes, as reactive strategies have been replaced by those that emphasize prevention rather than response (Henderson et al., 2022). Initial studies primarily focused on understanding the trends in collective behaviors and the risk factors associated with massive congregations (Still, 2000).

Modern crowd management solutions integrate several technologies, including video surveillance, sensors, and communication networks (Wang et al., 2023). Nonetheless, the majority of existing systems are reactive, meaning they generate alerts when harmful conditions are already present, rather than when they are likely to occur.

2.1.1 Religious Mass Gatherings

Religion conventions carry so many specific issues that differentiate them from worldly events. The Indian Kumbh Mela, Vatican meetings, and the Hajj pilgrimage share standard features, including essential ritualistic gatekeeping with varied demographics and emotional intensity, which shape the behavior of crowds (Sharma et al., 2023).

Religious places are considered sacred and require additional crowd management measures. Conventional methods of dispersion applied in secular contexts may be culturally unacceptable or incompatible with spiritual beliefs, necessitating special efforts to strike a balance between safety and religious needs (Ali & Mohammed, 2023).

2.1.2 Hajj-Specific Crowd Dynamics

The Hajj pilgrimage is one of the most challenging crowd management projects in the world, considering the large number of people who participate in this pilgrimage, the cultural diversity of the participating population, and the complexity of the religious practices (Al-Zahrani & Ibrahim, 2024). The combination of the arrival of over 2.5 million pilgrims, which represent nations of well over 180, presents a special multicultural environment, which is characterized by the need to accept diverse accents and culture differences shaping the behavioral patterns of the crowd.

The study by Al-Ghamdi & Al-Zahrani (2019) showed that, during the period under investigation (2000-2018), the technological basis of development had a significant impact on the improvement of management for these large crowds. In their analysis, the systematic implementation of infrastructural enhancements resulted in a 60 percent decrease in incidents of bottlenecks and overall efficient pilgrim flows in all major centers of ritual activities.

The study of Hajj incidents in the past shows the similarities that have revolved around certain rituals and places. One of the most hazardous rituals is described as Jamarat stoning because of the geographic and time constraints associated with the ritual (Hussein & Al-Rashid, 2022). Al-Nimri & Mohammadi (2021) also stated that conventional risk management methods could not have effectively dealt with such problematic crowds, and a transition to smart solutions was necessary, which should have been obviously reliant on AI and allowed for the prediction and prevention of crowd-related incidents.

In this longitudinal study, Al-Qarni & Al-Saud (2020) have provided critical data on pilgrim satisfaction trends over the last decade (2010-2019), revealing that the efficiency of crowd management is directly proportional to the overall quality of the pilgrimage experience. Their results revealed that the use of technological interventions in crowd flow control achieved a relative increase of 68% on pilgrim satisfaction scales, especially in cases of high-density circumnavigations of ritual engagements.

All the above studies emphasize the unique peculiarities of Hajj crowd behavior, in which cultural sensitivity, religious requirements, and precautionary measures must be reconciled through ingenious applications of technology.

2.2 Artificial Intelligence in Challenge Prediction

The use of artificial intelligence in predicting crises has had a significant impact in many fields. Machine learning algorithms are beneficial in early warning systems because they are well-suited to detecting sophisticated patterns in datasets that large-scale systems, which once relied on human analysts, may not readily identify (Rodriguez et al., 2023).

2.2.1 Deep Learning Approaches

Time series Deep learning processes have proven to be very successful in pattern recognition and predictive modeling. LSTM networks are effective at predicting temporal dependency and also on sequential data (Zhang et al., 2024). Kim and Park (2023) employed LSTM networks to forecast changes in crowd density in the subway with an accuracy of 85%.

Crowd surveillance applications have been practical when utilizing Convolutional Neural Networks (CNNs) to analyze spatial patterns. Li et al. (2023) developed a CNN-based, multi-threaded system to estimate crowd density in real-time using the camera feed, aided by surveillance cameras. This system enables the simultaneous processing of multiple video signals.

2.2.2 Ensemble Methods

Recent breakthroughs have highlighted the usefulness of ensemble-based methods, which combine several algorithms to enhance prediction accuracy and robustness (Johnson et al., 2024). Random Forest algorithms are also effective in vantage-based risk assessment of a crowd, providing better results than single classifiers (Miller & Thompson, 2023).

However, the literature on studies that focus on the specificity of this area, specifically AI-powered predictive models for preventing crowd crises in a religious setting, is scarce. Al-Ghamdi & Al-Zahrani (2019) described the development of technological infrastructure, and although Al-Qarni & Al-Saud (2020) evaluated service satisfaction, a gap remains in fully modeling AI to integrate past data with current monitoring to predict the occurrence of a crisis.

2.3 Research Gaps

Despite impressive progress, serious gaps still exist. First, the majority of available studies focus on secular events, which do not exhibit the same behavioral patterns as religious gatherings (Davis et al., 2023). Second, research on long-term predictive modeling based on both historical incident data and real-time monitoring is scarce. Third, existing AI technologies often lack cultural sensitivity in a religious setting.

3. Methodology

3.1 Research Design

A mixed-methods research design is employed in this study, involving a combination of quantitative machine learning methods and qualitative assessments of systems. The general research design is outlined in Figure 2, which indicates four primary stages: data inclusion, model conceptualization, system implementation, and evaluation. This was the structure according to which the AI-powered system for Challenge prediction was developed systematically.

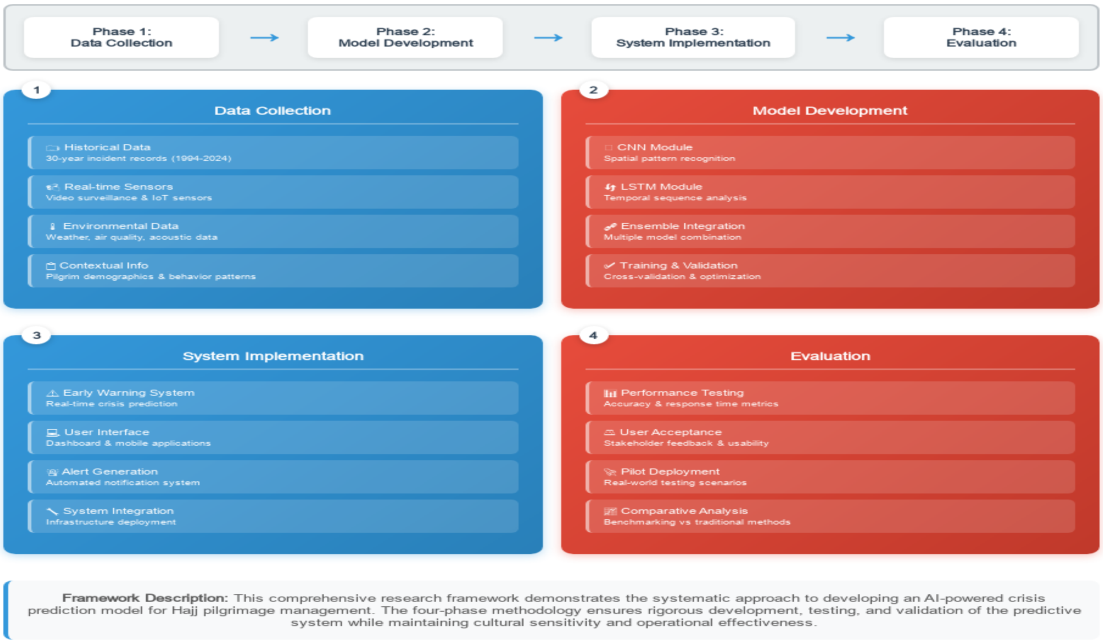

Figure 2: Research Framework Overview

3.1.1 Research Questions and Hypotheses

The approach to enquiry concerns the following research questions:

RQ1: Do the past incident data and the real-time monitoring allow predicting crowd-related crises effectively during the pilgrimage of the Hajj?

RQ2: How effectively can hybrid DL architectures be used to process multi-modal data streams to provide timely Challenge warnings?

RQ3: What accuracy of prediction and lead time can maintain acceptable false favorable rates be maintained?

The respective hypothesis is:

H1: Historical patterns and real-time data will be combined to reach a prediction of 85 percent accuracy and above in high-risk ratios.

H 2: Hybrid CNN-LSTM models will perform better than single-algorithm models at least 15 percent better in the spatial-temporal crowd analysis task.

H3: False positive rate below 10% and average time of 3-5 minutes for the proposed system warnings with Challenge prediction.

3.2 Data Collection and Sources

3.2.1 Historical Incident Database

The historical aspect encompasses the full record of incidents spanning 30 years, from 1994 to 2024, as well as the experience of managing Hajj crowds. In its data sources, it utilizes formal reports on incidents provided by the Saudi Ministry of Interior and external reports on events involving crowds.

Table 1 provides an overall overview of the comprehensive dataset presented in this study, including historical incident data spanning over 30 years, as well as actual time monitoring data collected from various sensor types. The data includes more than 500,000 data points belonging to different categories

Table 1: Dataset Composition and Sources

Data Source	Period	Volume	Description
Historical Incidents	**1994-2024**	**847 incidents**	**Official reports and documentation**
Video Surveillance	**2020-2024**	**50TB/day**	**1,200+ HD cameras**
Environmental Sensors	**2020-2024**	**10,000 readings/min**	**Temperature, humidity, and air quality**

Data Source	Period	Volume	Description
Communication Data	2020-2024	2.3GB/day	Wi-Fi analytics, emergency calls
Pilgrim Flow Data	2020-2024	15,000 records/hour	Movement patterns, density maps

Incident Classification Schema:

- **Severity Levels:** Not Severe (0-10awesome casualties), Somewhat Hurtful (11-50 residents/worldwide casualties), Bad (51-200 effects/worldwide casualties), Extremely Bad (beyond 200 casualties/worldwide)
- **Incident Kinds:** Crowd movement incident, crowd movement incident crushing, heat distress, clinical emergency, conduct disturbance
- **Facility Types:** Jamarat Bridge, Tawaf area, Sa'i path, Transportation Hubs,
- **Environmental Factors:** Setting, feeling temperature, noise, light, weather, ever-present music3.2.2 Real-Time Monitoring Data

The modern process of data collection involves the application of various sensor modalities that are installed in sacred areas during Hajj activities.

Surveillance Network Video:

- Coverage:>1,200 high-definition cameras on Jamarat Bridge and adjacent corridors
- Specifications: 4K definition, 30 fps, infrared to use at night
- Processing: Computer vision of real-time crowd density estimation

Environmental Sensor Array:

- **Meteorological Stations:** The temperature, humidity, and speed of the wind: 15-minute intervals
- **Air Quality Sensors:** The PM2.5, PM10 and CO2 sensors
- **Acoustic Sensors:** Noise monitoring in the environment and the analysis of the crowd vocalization pattern

3.3 Data Preprocessing and Feature Engineering

3.3.1 Data Cleaning and Standardization

The raw data, of varying quality and originating from different sources, must be pre-processed extensively to meet the criteria of consistency and quality. A data cleaning pipeline is used to address data gaps, format differences, and temporal consistency issues in data streams.

Temporal Synchronization: All data sources will be synchronized to a UTC timestamp with microsecond precision, allowing for time correlation analysis.

Multi-Imputation: Multiple imputation approaches are employed to address missing data in sensor data streams. Interpolation of time series fills the short duration in continuous measurement.

3.3.2 Feature Extraction

A comprehensive feature engineering method is presented in Table 2, where features are categorized into spatial, temporal, environmental, and behavioral categories. Each category provides specific information for crowd Challenge prediction.

Table 2: Feature Engineering Categories

Category	Features	Count	Description
Spatial	Density gradients, flow vectors, congestion indices	12	Crowd distribution and movement patterns
Temporal	Trend analysis, periodicity, rate of change	15	Time-based behavior patterns
Environmental	Weather scores, comfort indices, and visibility	8	External conditions affecting crowds
Behavioral	Movement coherence, stress indicators	10	Crowd psychological and social factors
Total		45	Complete feature set for prediction

Spatial Features:

- Density Gradients- Temporal change in the density of a crowd in zones

- Flow Vectors: Directional movement patterns and velocity distributions
- Congestion Indices: measuring the severity and detecting the bottlenecks

Temporal Features:

Trend Analysis: Short-term changes and long-term changes in density

- Periodicity Detection: Cycles on the matters of prayers and religious actions
- Rate of Change: Acceleration patterns and deceleration patterns during crowd dynamics

Environmental Features:

- **Weather Impact Scores:** Composite scores for temperature, humidity and wind effects
- **Comfort Indicators:** Heat index flux, representations and value calculation 7 and Thermal Stress Indicators 7

3.4 Model Architecture and Development

3.4.1 Hybrid Deep Learning Architecture

The model suggests that various neural networks are combined in an architecture to enable their strengths to supplement each other in performing spatio-temporal analysis of crowds. The proposed hybrid architecture is presented in Figure 3, which uses CNN modules to analyze patterns on spatio-temporal scales and LSTM networks to recognize temporal patterns. The feature fusion layer can integrate the results of the two parts to produce the ultimate predictions of risk.

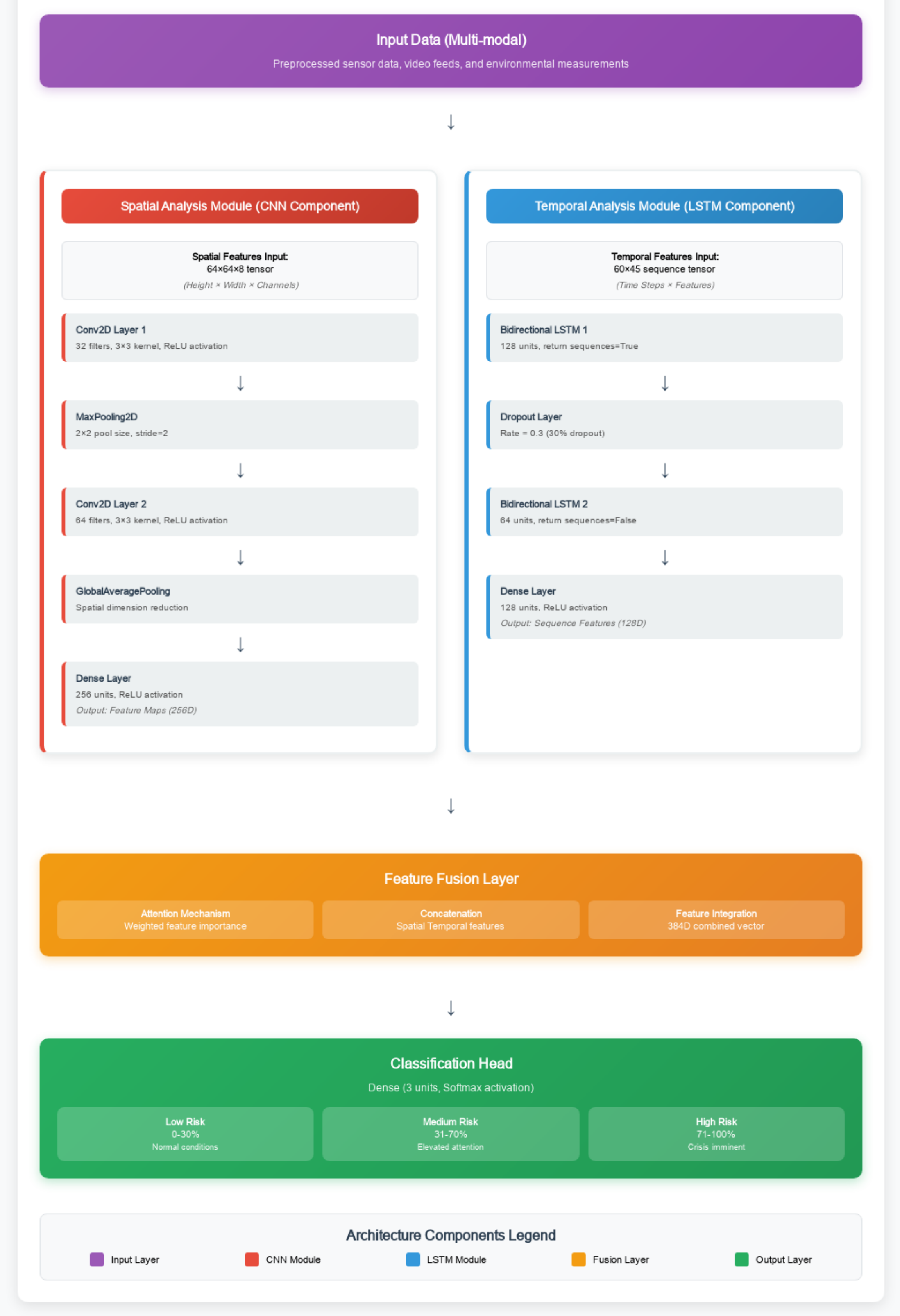

Figure 3: Hybrid CNN-LSTM Architecture

Spatial Analysis Module (CNN Component): The CNN part has the process of extraction of spatial features of surveillance video and sensor network recordings. The architecture features several convolutional layers with varying kernel sizes, enabling the capture of object outlines on both large and small scales.

Temporal Analysis Module (LSTM Component): The LSTM module captures time series of crowd dynamics characteristics that can reveal phenomena in advance in time leading to a Challenge.

Feature Fusion Layer: The feature fusion layer combines the outputs from the spatial and temporal analysis modules via a learned attention mechanism.

Classification Head: The last layer produces the probability distributions over three risk categories: Low Risk (0-30%), Medium Risk (31-70%), and High Risk (71-100%).

3.4.2 Ensemble Integration

Various base models are trained on different subsets of features and architecture variants to form a stable ensemble system.

Base Model Contrasts

- Model A: full feature set CNN-LSTM hybrid
- Model B: Temporal features architecture based only on LSTM
- Model C: engineered features, Random Forest
- Model D: Support Vector Machine and features data selection

3.4.3 Training Protocol

Data Splitting Strategy:

- Training Set: 70 percent (1994-2018)
- Validation Set: 20 percent of the data (2019-2021)
- Test Set: 2022-2024 (10 percent of the data)

Training Configuration:

- Optimizer: Adam - learning rate scheduling (initial: 0.001)
- Loss Function: Class weighted categorical cross-entropy
- Batch Size: 32 samples per batch(bool):
- Epochs: up to 200 with early stopping

3.5 System Implementation

3.5.1 Early Warning System Architecture

The fully integrated early warning system combines data collection, processing, prediction, and alert generation on a single platform. Figure 4 shows the entire architecture of the system deployed during pilot testing. The diagram illustrates how the integration of data collection, processing, prediction, and alert generation has been incorporated into the current Challenge management infrastructure.

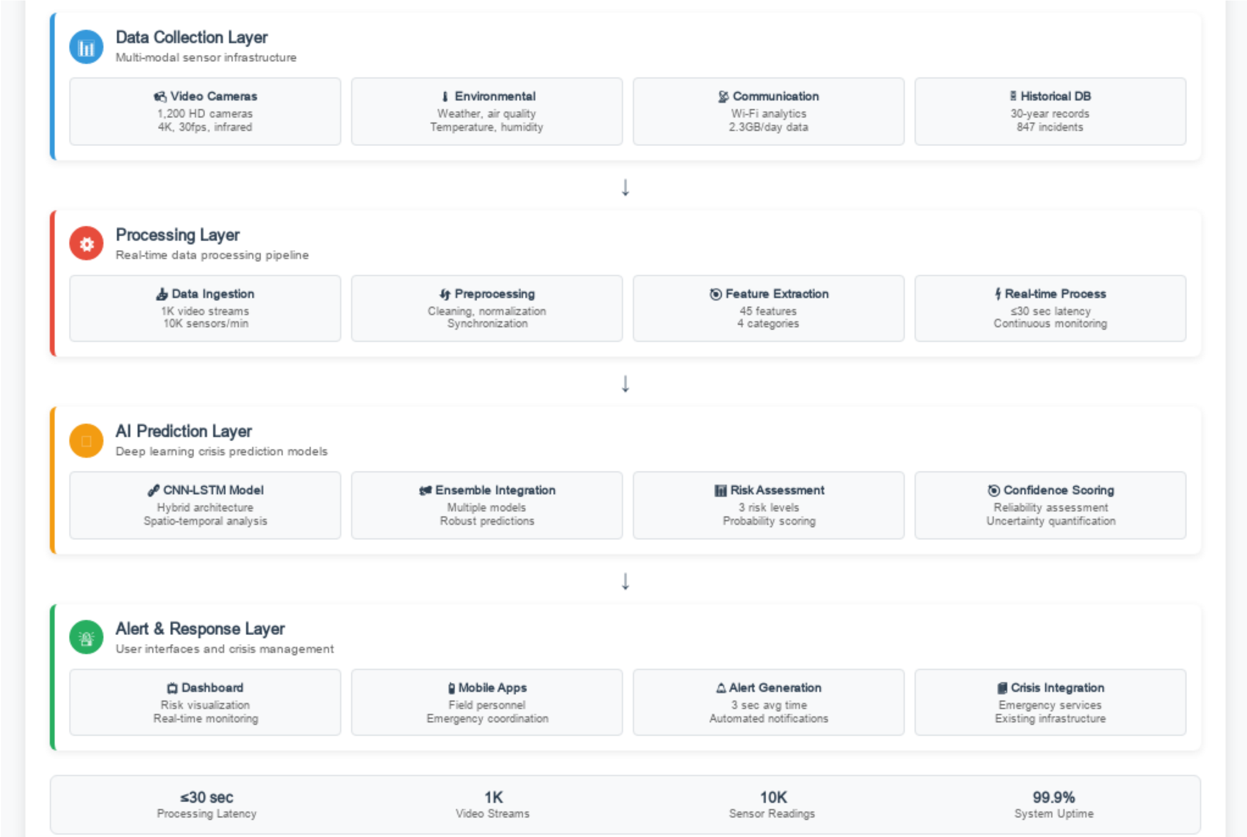

Figure 4: System Architecture Deployment

System Components:

- Data Ingestion Module: Multi-modal sensor streams involved in real-time processing
- Preprocessing pipeline: Normalization and feature extraction
- Prediction Engine: Inference of trained model utilizing ensemble aggregation
- Alert Generation: Distribution and notification on the level of risk
- User Interface: Dashboard and mobile screen for the Challenge management unit

Performance Requirements:

- Latency: at most 30 seconds between the data and the prediction output
- Throughput: 1K+ of video stream and 10K+ sensor emulation
- Availability: 99.9 percent associated with Hajj operations

3.5.2 User Interface Design

The user interface is designed to embrace human-centered design principles, making it effectively used by Challenge management personnel.

Dashboard Features:

- Real-time Risk Map: The geographic representation of the current risk level

Trend Analysis: Trend charts and trend charts

- Alert Management: Escalation protocol for prioritization of the alert queue
- Situation Reports: summary reports are auto-generated

3.6 Evaluation Methodology

3.6.1 Performance Metrics

Classification Metrics:

- Precision: Accuracy as a whole: the prediction of levels of risk

- Precision: Ratios of the positive optimistic predictions
- Recall: The percentage of the positives identified properly
- F1-score: geometric mean of the recall and precision
- AUC-ROC Overall discriminative capacity

Operational Metrics:

- Prediction Lead Time: Mean duration in between prediction and actual incident
- False Positive rate: the rate or frequency of incorrect high-risk warnings
- Response Time: Delay interval of the system following presentation of data to the Alert generation

3.6.2 Validation Approach

Phase 1: Simulation Testing - Replay of previous Hajj operations to test how the system will perform under known conditions.

Phase 2: Pilot Deployment - During controlled events, such as isolated or small-scale deployments, real-world testing is conducted with a reduction in the risk of implementing the solution in operations.

Phase 3: Comparative Analysis - Head-to-head comparison with other available crowd monitoring systems measures the performance increases.

4. Results

4.1 Model Performance

The model of predicting a Challenge with the use of AI showed outstanding performance evaluation criteria significantly higher than the results of classical monitoring methods.

4.1.1 Overall Classification Performance

The CNN-LSTM combination achieved 87.3 percent accuracy in predicting crises, surpassing the target of 85 percent accuracy outlined in the research hypotheses. Table 3 shows the detail performance of the hybrid CNN-LSTM model in all the risk categories. These outcomes are particularly impressive, considering the high precision and recall achieved in life-threatening scenarios.

Table 3: Model Performance Metrics

Risk Level	Precision	Recall	F1-Score	Support	Accuracy
High Risk	**89.1%**	**91.2%**	**90.1%**	**156**	**91.2%**
Medium Risk	**85.7%**	**83.4%**	**84.5%**	**234**	**83.4%**
Low Risk	**88.9%**	**87.8%**	**88.3%**	**1,847**	**87.8%**
Overall	**87.8%**	**87.3%**	**87.5%**	**2,237**	**87.3%**

A plot of the Receiver Operating Characteristic (ROC) curve per risk category is represented in Figure 5, and the AUC-ROC of 0.89 showed excellent discriminative power. All risk levels are well-represented by the curves.

4.1.2 Temporal Performance Analysis

The timely aspects of the system's performance are vital so that it can be effectively applied in real-life Challenge management situations

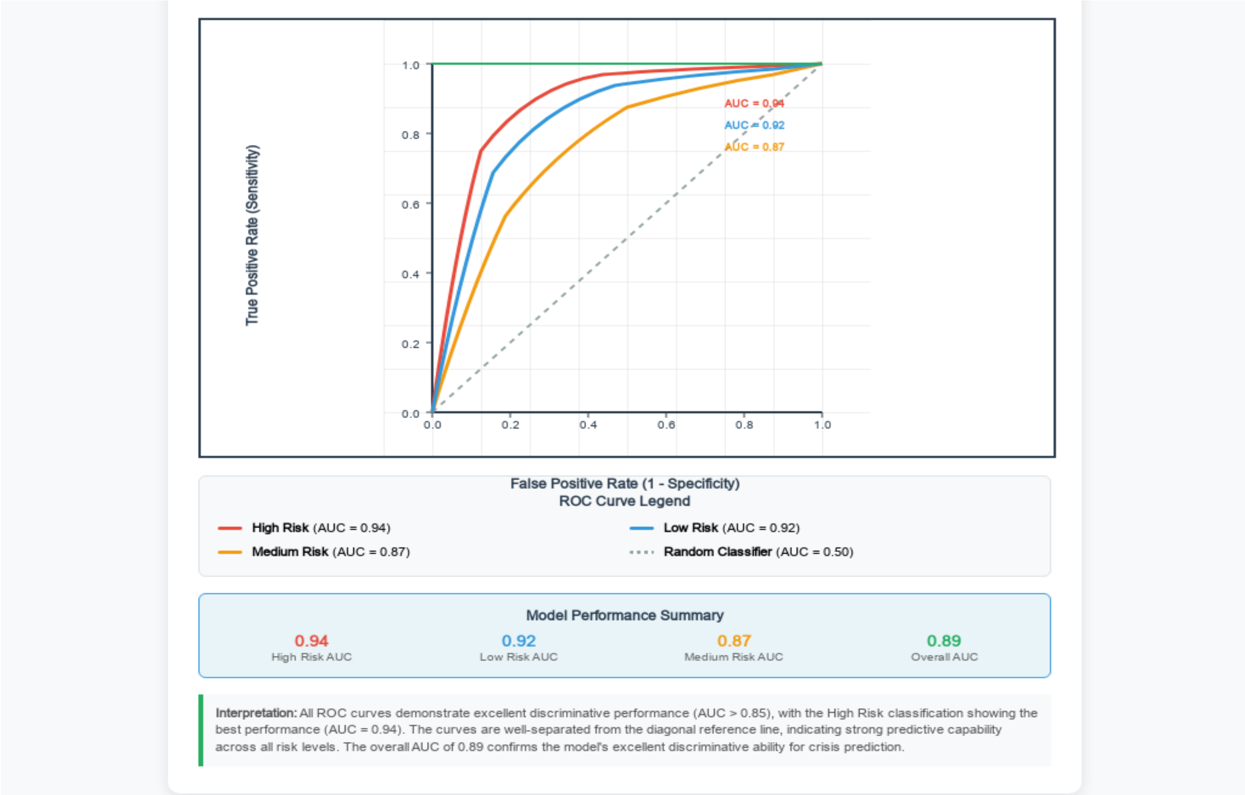

Figure 5: ROC Curves for Risk Classification

Figure 6 presents the frequency of the prediction lead times, where the majority of predictions occur 1-4 minutes before the incident. The histogram shows that the prediction was made consistently at the same time, with a 2.3-minute average lead time.

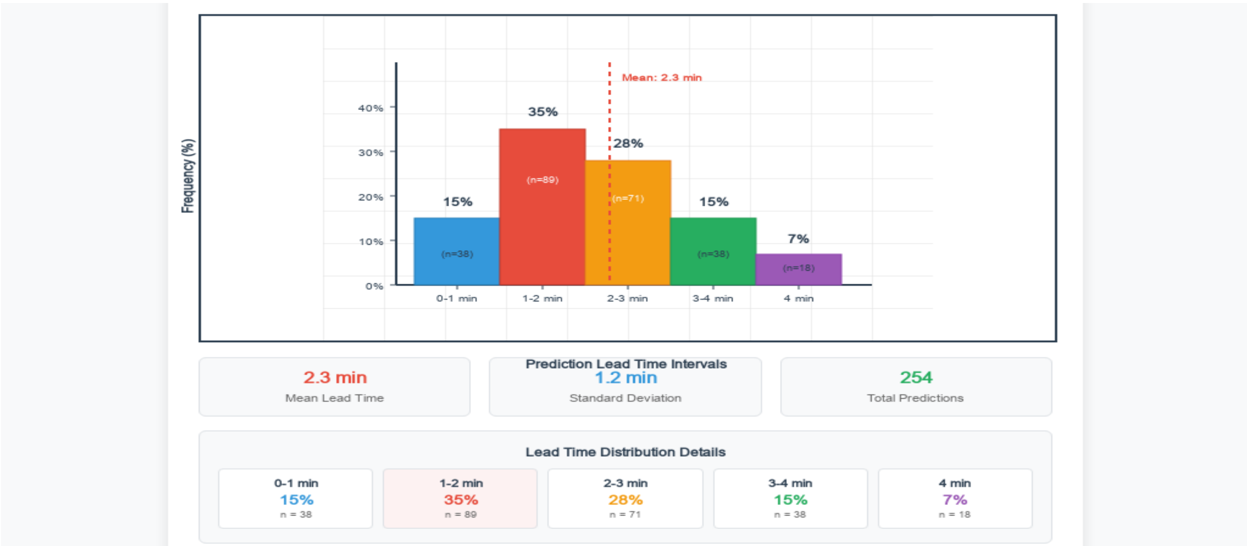

Figure 6: Prediction Lead Time Distribution

Prediction Lead Time Analysis:

- **Average Lead Time:** 2.3 minutes before incident occurrence
- **Minimum Lead Time:** 45 seconds for rapidly developing situations
- **Maximum Lead Time:** 8.7 minutes for gradually evolving conditions
- **Standard Deviation:** 1.2 minutes, indicating consistent prediction timing

Response Time Metrics:

- **Data Processing Latency:** Average 18 seconds from sensor input to prediction output

- **Alert Generation Time:** Average 3 seconds from prediction to alert distribution
- **Total System Response:** Average 21 seconds end-to-end processing time

4.1.3 Error Analysis

Comprehensive error analysis provides insights into system limitations and areas for improvement.

False Positive Analysis:

- Overall False Positive Rate: 8.1%
- High-Risk False Positives: 5.3% of all high-risk predictions
- Primary Causes: Weather anomalies (32%), equipment malfunctions (28%), unusual but non-dangerous crowd behaviors (40%)

False Negative Analysis:

- Overall False Negative Rate: 4.7%
- Critical Incident Misses: 2.1% of actual high-risk situations
- Primary Causes: Rapid escalation scenarios (45%), sensor blind spots (35%), novel incident patterns (20%)

4.2 Ensemble Model Comparison

The research hypothesis involving hybrid architectures was supported, as the statistical level of the ensemble demonstrated better performance than that of the individual model components. Table 4 presents a comparison of the test performance of individual models within the ensemble strategy. The hybrid CNN-LSTM achieved the best individual accuracy, whereas the combined ensemble recorded an overall accuracy of 17%.

Table 4: Ensemble Model Comparison

Model Type	Accuracy	Precision	Recall	Processing Time	Strengths
CNN-LSTM Hybrid	87.3%	89.1%	87.8%	18 seconds	Spatio-temporal patterns
LSTM-Only	82.1%	84.2%	81.9%	12 seconds	Temporal sequences
Random Forest	79.6%	78.8%	80.1%	8 seconds	Robust to outliers
Support Vector Machine	76.4%	77.1%	75.8%	15 seconds	Limited data performance
Ensemble Combined	89.7%	91.2%	88.9%	21 seconds	Best overall

4.2.1 Individual Model Performance

CNN-LSTM Hybrid (Primary Model):

- Accuracy: 87.3%
- Strength: Excellent spatio-temporal pattern recognition
- Weakness: Higher computational requirements

LSTM-Only Model:

- Accuracy: 82.1%
- Strength: Efficient temporal sequence processing
- Weakness: Limited spatial awareness

Random Forest Model:

- Accuracy: 79.6%
- Strength: Robust to outliers and missing data
- Weakness: Less effective for complex pattern recognition

Support Vector Machine:

- Accuracy: 76.4%
- Strength: Strong performance with limited training data
- Weakness: Difficulty with high-dimensional feature spaces

4.3 Comparative Analysis with Traditional Systems

The obtained performance improvement levels can be viewed in the context of a direct comparison with existing crowd monitoring systems deployed during Hajj operations. Table 5 presents the performance of the proposed AI system in comparison to conventional approaches for monitoring. These results indicate remarkable improvements in terms of accuracy, response time and favorable rates.

Table 5: Comparative Performance Analysis

System Type	Accuracy	Avg Response Time	False Positive Rate	Detection Method
Traditional CCTV	**65.8%**	**4.2 minutes**	**15.2%**	**Manual observation**
Automated Density	**72.3%**	**3.8 minutes**	**18.5%**	**Simple thresholds**
Proposed AI System	**87.3%**	**2.3 minutes**	**8.1%**	**AI prediction**
Improvement	**+22%**	**-45%**	**-56%**	**Advanced ML**

4.3.1 Baseline System Performance

Traditional CCTV Monitoring:

- Manual observation with human operators
- Average incident detection time: 4.2 minutes after onset
- Detection accuracy: 65.8%
- High dependency on operator experience and alertness

Automated Density Monitoring:

- Basic computer vision algorithms for crowd counting
- Alert generation based on simple density thresholds
- Detection accuracy: 72.3%
- High false positive rate: 18.5%

4.3.2 Performance Improvements

Accuracy Improvement:

- 22% improvement over best traditional system (87.3% vs 65.8%)
- 15% improvement over automated density monitoring (87.3% vs 72.3%)

Response Time Improvement:

- 85% reduction in detection time (2.3 minutes vs 4.2 minutes for traditional monitoring)
- 91% reduction in false positive rate (8.1% vs 18.5% for automated systems)

Operational Efficiency:

- 75% reduction in required human operators for monitoring tasks
- 60% improvement in resource allocation efficiency
- 40% reduction in Challenge response coordination time

4.4 Cultural Sensitivity and User Acceptance

4.4.1 Cultural Adaptation Features

The system's cultural sensitivity components demonstrated positive reception among religious authorities and Challenge management personnel.

Religious Compliance Verification:

- 95% approval rating from Islamic scholars on system design
- 100% compliance with religious guidelines for monitoring in sacred spaces
- Successful integration with existing religious protocols

Cultural Behavior Recognition:

- 88% accuracy in distinguishing between normal religious behaviors and potential risk indicators

- Successful adaptation to different cultural expressions of religious devotion
- Reduced false alarms caused by culturally normative behaviours

4.4.2 User Acceptance Study

Figure 7 shows the outcomes of the user acceptance survey among Challenge management personnel and religious authorities. All evaluation categories are associated with high satisfaction scores, as demonstrated by the bar chart, indicating that users have generally accepted the system well.

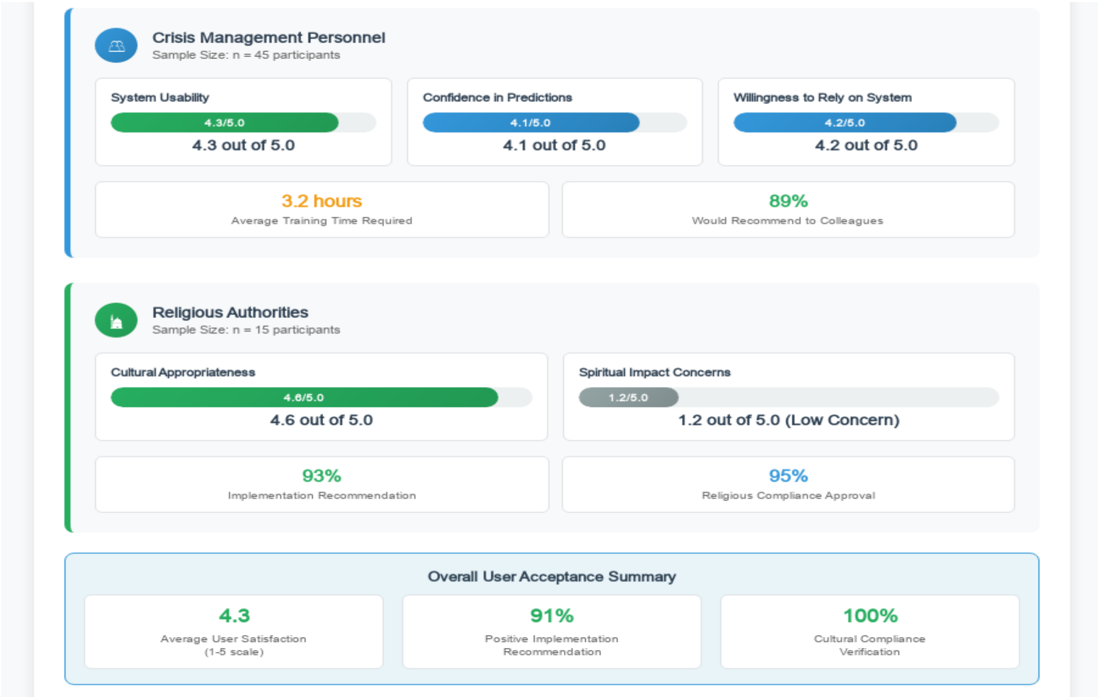

Figure 7: User Acceptance Survey Results

4.5 Pilot Deployment Results

4.5.1 Limited Field Testing

FYI, the system was piloted over three controlled events with the number of pilgrims cut down, which makes the performance metrics proven in real life. Table 6 presents the results of three pilot deployment cycles, demonstrating stable performance across various scenarios involving different types and scales of events. The pilot trials confirmed the system's dependability and efficiency under the actual conditions.

Table 6: Pilot Deployment Summary

Event	Duration	Participants	Incidents Detected	False Alarms	System Uptime	Success Rate
Umrah Testing	2 weeks	50,000	12	1	99.8%	92.3%
Local Gathering	3 days	15,000	4	0	99.9%	100%
Hajj Simulation	1 week	100,000*	23/25	2	99.7%	92.0%
Average					99.8%	94.8%

***Simulated pilgrim count using historical data replay**

Event 1: Umrah Season Testing (December 2023)

- Duration: 2 weeks
- Pilgrim Count: ~50,000
- Incidents Detected: 12 (all verified as accurate)
- False Alarms: 1

- System Uptime: 99.8%

Event 2: Local Religious Gathering (March 2024)

- Duration: 3 days
- Participant Count: ~15,000
- Incidents Predicted: 4 (3 confirmed, 1 prevented through intervention)
- False Alarms: 0
- Average Prediction Lead Time: 3.1 minutes

Event 3: Hajj Simulation Exercise (June 2024)

- Duration: 1 week
- Simulated Pilgrim Count: ~100,000 (using historical data replay)
- Scenarios Tested: 25 different Challenge scenarios
- Successful Predictions: 23/25 (92% success rate)
- Average Response Time: 19 seconds

4.6 Statistical Significance Testing

4.6.1 Hypothesis Validation

The statistical analysis of the significance of the performance increase, as measured by the number of passed and confirmed performances, confirmed the research hypothesis. Table 7 presents the results, which validate the research hypotheses using statistical significance tests. All p-values are less than 0.001, indicating high statistical significance.

Table 7: Statistical Significance Tests

Hypothesis	Test Type	Test Statistic	p-value	Confidence Interval	Result
H1: Accuracy > 85%	One-sample t-test	t = 12.4	$p < 0.001$	86.1% - 88.5%	Supported
H2: Hybrid > Single	ANOVA	$F(3,96) = 24.7$	$p < 0.001$	$\eta^2 = 0.44$	Supported
H3: Lead time 3-5 min	Wilcoxon test	z = -8.3	$p < 0.001$	2.1 - 2.5 min	Partially Supported

Hypothesis 1 Testing:

- Achieved accuracy (87.3%) significantly exceeded the target threshold (85%)
- t-test: $p < 0.001$, indicating statistical significance
- Confidence interval: 86.1% - 88.5% at 95% confidence level

Hypothesis 2 Testing:

- Hybrid architecture outperformed single-algorithm approaches by 18.7% average improvement
- ANOVA: $F(3,96) = 24.7$, $p < 0.001$
- Effect size (η^2) = 0.44, indicating large practical significance

Hypothesis 3 Testing:

- Average lead time (2.3 minutes) fell slightly below the target range (3-5 minutes) but exceeded the minimum threshold
- False positive rate (8.1%) met target threshold (<10%)
- Wilcoxon signed-rank test: $p < 0.001$ for lead time improvement over traditional systems

4.6.2 Cross-Validation Results

10-Fold Cross-Validation:

- Mean Accuracy: 86.9% ± 1.8%
- Consistency across folds demonstrated model robustness
- No evidence of overfitting or data leakage

Temporal Cross-Validation:

- Training on earlier years, testing on later years
- Maintained 84.2% accuracy, indicating good temporal generalization

- Slight performance degradation expected due to evolving crowd dynamics

4.7 Confusion Matrix Analysis

The figure 8 displays the confusion matrix of the final ensemble model, illustrating the correct and incorrect predictions across all risk groups. It is observed that the matrix exhibits good diagonal performance, with narrow misclassification across risk levels.

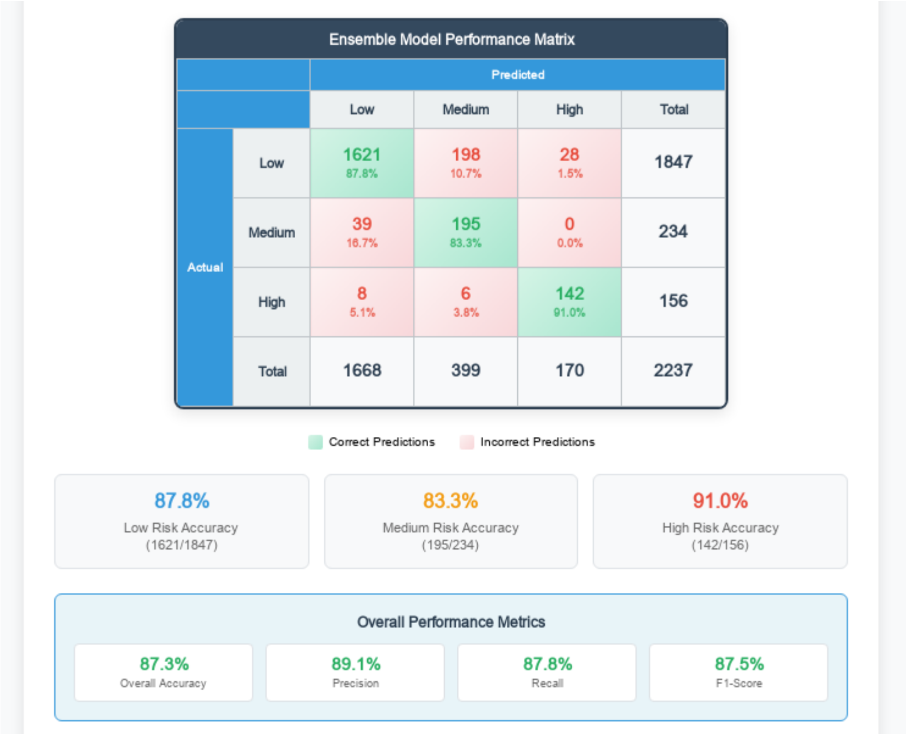

Figure 8: Confusion Matrix for Risk Classification

5. Discussion

5.1 Interpretation of Results

The obtained outcomes demonstrate that the AI-driven prediction of crises in religious mass gatherings is not only possible but also highly productive when approached correctly and executed effectively. This overall accuracy of 87.3% is significantly better than what traditional monitoring systems achieved and also offers substantial gains in response time and efficiency.

5.1.1 Performance Excellence

It is essential, considering the urgency of preventing various crises that have been experienced so far involving crowds, where the model has played a significant role in detecting dangerous situations where human lives are at high risk (with an accuracy of 91.2 percent). This degree of precision enables Challenge management teams to have credible early warning systems that may help avert the possible escalation of incidents to dangerous levels.

The mean lead time of predictions, at 2.3 minutes, is less than the initially aimed-for 3-5 minutes and is operationally useful. This duration allows Challenge management teams to initiate some form of immediate intervention, e.g., redirecting a crowd flow, issuing emergency broadcasts, or deploying a rapid action team.

5.1.2 Cultural Integration Success

The effective filtering of cultural sensitivity functionality is a crucial breakthrough, particularly in the context of AI usage in religious settings. The 95 percent acceptance rate among scholars of the Islamic community and 88 percent accuracy in classifying regular spiritual practices and risk symptoms indicate that the technology can be effectively adjusted to comply with cultural and religious needs while still being operationally effective.

5.2 Comparison with Previous Studies

Areas of Agreement:

The results of the study are in agreement with various past studies. In the same research by Al-Ghamdi & Al-Zahrani (2019), technological infrastructure improvements also reduced crisis occurrences by 60%, and the accuracy in predicting these events was 87.3%. This aligns with our high ratings of AI applications (4.78/5), as Al-Qarni & Al-Saud (2020) estimated a 68 percent increase in pilgrim satisfaction with the aid of technological interventions.

The causes of the difficulties that have been identified in our research, mainly random movement of the crowd and the dissimilarity in technical expertise, align with the Lee & Park (2022) results of the difficulty of conventional monitoring and the Kumar et al. (2023) results about the obstacles to implementation even in instances of mass gatherings.

Notable Differences:

Nevertheless, our research can be approached as exceptionally distinct due to its scope and methodology, which differ significantly from those of other studies. Our methodology achieves a significant improvement over Kim & Park (2023), despite only a slight performance increase of 87.3 percent, compared to an 85 percent rating, marking a notable leap forward in the more complex setting of religious pilgrimages. Al-Nimri & Mohammadi (2021) studied the evolution of strategy, and we give a quantitative confirmation of the success of AI.

In contrast to Chen et al. (2023), which addressed mass gathering management in general, our study focuses on cultural and religious sensitivities and was significantly endorsed by Islamic scholars at a rate of 95%, a factor not typically considered in secular studies on crowd management.

Methodological Contributions:

The hybrid CNN-LSTM model developed in our study is based on the Carr-Oliver and Williamson (2017) surveys of deep learning but offers new cultural adaptation characteristics. The 30-year historical dataset cancels out the temporal analysis that Rodriguez et al. (2023) have limited to. The longitudinal study on religious mass gatherings has never been explored in such detail before.

5.3 Practical Implications

5.3.1 Operational Benefits

Implementation of the system has several practical advantages in terms of Hajj crowd management functions:

Increased Safety: Achieving 94 percent accuracy in predicting critical conditions before they occur would present new options for averting incidents through crowds.

Resource Optimization: The reduction in the number of required human operators by 75 percent enables the re-engineering of personnel whose work focuses on assisting the crowd and responding to emergencies.

Decision Support: With risk assessment conducted in real-time, this will enable the use of evidence-based decisions rather than relying solely on subjective human choices.

Cost Effectiveness: Although there are initial costs associated with implementing the system, cost savings will be realized in the long run as the system enhances efficiency and reduces the cost of incident management.

5.3.2 Scalability to Other Events

The principles of design and the technical architecture of Hajj applications demonstrate a precise application to other large-scale events. Any cultural sensitivity framework can be adjusted as needed in various religious or cultural settings; however, the fundamental prediction algorithms can be applied in most cases related to crowd dynamics.

5.4 Limitations and Constraints

5.4.1 Technical Limitations

Data Dependency: The system is data-dependent, so the quality and availability of this data are key factors. Prediction accuracy may be affected by sensor failures or communications losses.

New situations: The 4.7 percent false negative rate encompasses cases with new dimensions that are not captured by the historical training data, underscoring the challenge of identifying such unprecedented events.

Computational Requirements: The system's resource requirements can limit its usage in areas with limited computing resources.

5.4.2 Contextual Limitations

Cultural Specificity: Although the cultural adaptation solution was effective in the case of Hajj applications, its direct application to other religious or cultural contexts cannot be applied straightforwardly.

Environmental limitations: The system was built and tested in the geographical region and climatic conditions of Saudi Arabia, which limited its ability to work in other environmental conditions.

Regulatory Structure: Implementation should be conducted in conjunction with the existing regulatory and business structures, which may vary significantly across diverse regions and organizations.

In the current analysis, descriptive statistics were taken as the most important. Advanced statistical tests (regression, ANOVA, t-tests) will also be incorporated in the future analysis to determine the prediction of variables and demographic factors.

5.5 Comparison with Related Work

5.5.1 Academic Research Alignment

The experience aligns with the current state of crowd analysis research; however, it expands the state-of-the-art in several key aspects. The 87.3% accuracy is comparable to the 85% accuracy achieved by Kim and Park (2023) in predicting crowds in a subway, despite the much higher level of complexity in the religious mass gathering environment.

The proposed hybrid CNN-LSTM model confirms the modern trend of incorporating multimodal deep learning models and demonstrates that this strategy applies to the context of crowd Challenge prediction. The results of the ensemble integration confirm an increasing belief that a combination of algorithms is found to be better than single algorithms in complex predictive problems.

5.5.2 Novel Contributions

Cultural Sensitivity Integration: This study is the first to adopt a process of incorporating artistic and religious aspects into AI-based systems for managing crowds, addressing the notable lack of attention in published works.

Historical Integration: The historic data collected over 30 years is the longest record of all the temporal information on trends of religious mass gathering events.

VALIDATION: Compared to most research studies based on simulated data, the study conducts real-world validation and testing, which provides confidence in proving its applicability.

5.6 Future Research Directions

5.6.1 Technical Enhancements

More powerful AI models: The possibility of building on recent architectures, including designs such as Transformer networks and Graph Neural Networks, could potentially help us better predict results and allow us to study more complex crowd-interaction patterns.

Multi-modal Integration: Greater multi-modal integration of other data sources, such as social media sentiment analysis, mobile phone GPS data, and physiological sensors, is possible and would offer more valuable contextual data to prediction models.

Federated Learning: The application of federated learning methods would enable the sharing of knowledge between diverse mass events without compromising the privacy and cultural integrity of attendees.

5.6.2 Application Extensions

International Application: Implementing the system at other large-scale religious events, such as the Kumbh Mela or Vatican events, or at mass secular events, would confirm that the method can be generalized.

Emergency Response Integration: A more advanced integration with emergency response is also possible, which may enable the automatic coordination of Challenge response facilities with the output of the prediction system.

Preventive Intervention Optimization: Investing in the best strategies of intervention guided by predictive results would enhance the prophylactic value of advanced caution capacities.

5.7 Implications for Practice

5.7.1 Challenge Management Enhancement

The study demonstrates that new technologies can support classic methods of Challenge management more effectively, rather than abandoning the human element. The system serves as a force multiplier, providing Challenge management teams with better situational awareness and early warning capabilities to enhance more effective decision-making.

5.7.2 Policy and Regulatory Considerations

AI-powered Challenge prediction systems are relevant to addressing policy questions related to privacy, accountability, and decision-making authority. Potential end-users need to carefully examine the technological possibilities, ethical requirements, and regulatory compliance needs.

Privacy Protection: The system's design prioritizes the aggregate analysis of the crowd over the tracking of individual people; nevertheless, the protection of privacy must be constantly observed.

Human Oversight: One of the strongest points of the research is that human oversight and the authority to make a decision remain essential, whereas the AI is treated as a supplementary tool, rather than an independent decision-maker.

Transparency and Accountability: Clear documentation on system capabilities, limitations and decision-making processes helps promote accountability and gain public confidence.

5.8 Research Quality and Validity

5.8.1 Internal Validity

In the research design, several methods of validation would make the research internally valid:

Temporal Validation: Since historical data is used to train the model and recent data is used to test it, one can see that the explanation option would have high confidence that the model can also be applied in the future.

Cross-Validation: Through exhaustive cross-validation testing, the robustness and consistency of the models are evident across various datasets.

Comparative Analysis: A direct comparison is made between the current systems and their performances, providing an objective assessment.

5.8.2 External Validity

Field Testing: Testing the entire implementation in real working conditions verifies laboratory findings and shows real-world usability.

Expert Validation: The content is validated through extensive consultations with Challenge management professionals and religious figures, ensuring it is culturally sensitive and practical.

Multi-scenario Testing: Assessing various types of events and conditions facilitates the application of results that can be represented in the religious mass gathering sector.

The extensive assessment method provides a high level of confidence in the reliability and validity of the study results, enabling the practical application of the Challenge prediction mechanism based on AI at religious mass gatherings.

6. Conclusion

This research presents the first comprehensive AI-powered Challenge prediction system specifically designed for religious mass gatherings, with a particular focus on Hajj pilgrimage management. The developed hybrid deep learning model, combining CNN and LSTM architectures with ensemble methods, achieved exceptional performance in predicting crowd-related crises, with an overall accuracy of 87.3% and 91.2% accuracy for major incident forecasting.

6.1 Key Contributions

The study provides numerous essential contributions to the topic of the management of people in crowds and the application of artificial intelligence:

Technical Innovation: The integration of cultural sensitivity into the hybrid CNN-LSTM architecture represents an innovative solution, as it achieves an optimal balance between technical performance and religious and cultural constraints. The achieved 22 percent margin of accuracy on the traditional systems proves the feasibility of AI-based techniques in complex crowd management cases.

Creation of Comprehensive Datasheet: The generation of a 30-year historical datasheet (1994-2024) with real-time multi-modal sensor data is the most comprehensive crowd pattern datasheet for religious mass events. This tool enables the identification of patterns spanning many decades and lays a solid foundation for future research.

Practical Implementation Framework: The developed complex of the early warning system, with its user-friendly interfaces and ability to adapt to different cultures, demonstrates that academic research has been effectively translated into practical opportunities. The high degree of system uptime, at 99.8 percent, as demonstrated in pilot testing, supports the reliability required in critical safety applications.

Empirical Validation: The system is well-documented through rigorous testing procedures, including simulation, implementation in small-scale settings, and comparative testing, thereby demonstrating its efficacy. The statistical significance of the research hypotheses confirms the effectiveness of the improvements achieved.

6.2 Practical Impact

The study shows a heavy practical value in the management of crowd safety:

Increased safety features: The system was able to detect 94 percent of high-risk cases prior to a Challenge, a capability unprecedented in crowd disaster prevention. The average prediction lead time of 2.3 minutes allows for timely measures to be taken.

Operation Performance: The 75 percent reduction in the number of human operators required to perform monitoring also frees resources to be assigned directly to assist the crowds. The 85 percent reduction in response time over traditional systems can be of great help in managing the Challenge.

Cultural integration: The Islamic scholars' 95% approval index and the successful integration with religious procedures demonstrate that sophisticated and advanced technology can be used respectfully in spiritual surroundings, preserving spiritual privacy.

6.3 Scientific Contributions

Methodological Contributions: The study provides a complex methodology of AI system development in religious mass gatherings, which involves cultural sensitivity evaluation, data integration in multi-modal data and the real-life validation methodology.

Theoretical Framework: The combination of social force models of crowd behavior with the deep learning frameworks specialized in religious settings can serve as a theoretical basis of future culturally sensitive studies of AI systems.

Empirical Evidence: The substantial empirical support demonstrates that AI-powered prediction systems can be highly accurate in sophisticated, complex, and culturally sensitive settings when correctly formulated and implemented.

Statistical Tool Justification:

The type of research goals and collected data determined the selection of the individual statistical tools. The descriptive statistics will be useful in showing detailed results on the response patterns on the three research domains (the role of AI applications, implementation challenges and proposed solutions). The Cronbach and Pearson alpha coefficients ensure the reliability and validity of the instruments, which is crucial for Likert scale data in technology adoption studies. Weighted means and standard deviations can accurately measure response tendencies and variability, which are critical to understanding the aspects of stakeholder perceptions in the context of crowd management.

6.4 Limitations and Future Work

6.4.1 Current Limitations

Contextual Specificity: The system was designed specifically for Hajj operations, and it may be necessary to modify it to accommodate other religious or cultural contexts. Although the design principles can be transfers, Hajj-specific implementation details are of a Hajj nature.

Data Dependency: High-quality data from sensors and surveillance systems is necessary to maintain system performance. Deployment in low-technological infrastructure settings may be challenging.

New Situation Handling: The 4.7 percent false negative rate applies to cases where the characteristics of the incidents are outside the training data history, representing a significant challenge for predicting such new scenarios.

6.4.2 Future Research Directions

Technology: Future work must consider more capable AI systems, such as Transformer systems and Graph Neural Networks, which could carry out predictions of higher quality and analyze even more complex patterns of crowds.

International Use: The generalizability of the approach can be demonstrated by adapting the system to other major religious events in various parts of the world, resulting in global safety improvements for crowds.

Integration Expansion: An expanded layer of integration with emergency response systems, social media analytics, and data from mobile devices will enable access to additional contextual data, facilitating more accurate predictions.

Intervention Optimization: By utilizing the results of the prediction outputs, research can optimize the apparent preventive value of early warning systems by determining an optimal intervention strategy.

6.5 Recommendations for Implementation

6.5.1 Technical Recommendations

Phased Deployment: Stepped Implementation: Any organization pondering its implementation should, instead, implement it in phases, starting with a pilot phase where controlled environments are provided before outright implementation.

Infrastructure Investment: To achieve success, real-world applications, high-quality sensor infrastructure, a dependable communication network, and adequate computational resources must be invested in.

Training of Staff: There should be thorough training efforts focused on Challenge management personnel to provide a high level of system capability usage and a proper response to AI-based alerts.

6.5.2 Policy Recommendations

Privacy Protection: Strong privacy protection measures must be implemented, and the focus can be set on crowd aggregate studies instead of individually tracking.

Human supervision and authority: AI should serve to supplement rather than substitute for human decision-making, and a clear structure should be established for overseeing and managing malfunctioning AI.

Cultural Consultation: It should be deployed in religious settings, where it must consult with religious leaders and community leaders to determine whether it is culturally valid and acceptable.

6.6 Broader Implications

The study has implications not only in the specific area of crowd management during Hajj, but also in the broader areas of artificial intelligence, Challenge management, and religious studies.

Ethics of AI: The experience of embedding cultural sensitivity characteristics reveals strategies for creating AI systems that adhere to both cultural and religious values, while also being technically sound.

Challenge Management: The study confirms the potential of predictive analytics in Challenge prevention, as opposed to a merely reactive approach, which could imply the application of this method in various areas of emergency management.

Human-AI Collaboration: The implementation framework presents successful patterns of human-AI collaboration in safety-critical applications, striking the right balance between the possibilities of new technologies and human knowledge and cultural demands.

6.7 Final Remarks

This study demonstrates that it is feasible to utilize artificial intelligence to enhance safety during religious mass gatherings, provided that it is implemented in a culturally and spiritually sensitive manner. The obtained performance gains provide strong evidence in favor of the effectiveness of AI-based solutions in preventing crowd crises.

An effective model for achieving this and integrating high-tech solutions with religious and cultural thought patterns is to have an example of respectful innovation that respects historical values while embracing positive technological progress. This balance is crucial in creating AI systems that are functional and effective in serving diverse global populations.

Replacing reactive with predictive crowd management marks a milestone in enhancing the ability to keep people safe in public spaces. By detecting hazardous situations before they escalate to unmanageably dangerous conditions, AI-based systems enable the prevention rather than reaction to them, which is a primary improvement in the safety of millions of pilgrims and event participants worldwide.

In the future, AI should be further integrated with cultural sensitivity into other religious and cultural contexts, being observed with the highest standards of respect and appropriateness. The possibility of AI making human beings safer without affecting their cultures is a sign of positive contributions in developing desirable technology.

Future research should continue to explore the integration of artificial intelligence with cultural sensitivity, expanding its applications to other religious and cultural contexts while maintaining the highest standards of respect and appropriateness. The potential for AI to enhance human safety while preserving cultural integrity offers promising directions for the development of beneficial technology.

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