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AI-Powered Ground Vibration Prediction System Using Quantitative Sensors and Qualitative Observations

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Abstract - To mitigate construction, industrial process, and seismic risks, in this paper, we introduce a hybrid AI-based vibration monitoring system. The system records multi-dimensional vibration data and analyzes it using a deep learning pipeline to forecast vibration pattern and magnitude. It employs a mechanically optimized beam for improved sensitivity with reduced noise, and a six-axis IMU containing an accelerometer and gyroscope. Its real-time alert in early warning mode is better than conventional methods by offering up to 5x signal gain and enhanced micro-vibration detection. Scalable and cost-effective design in its support encompasses urban planning, seismic resilience, and industrial safety.

Keywords - Ground Vibration Prediction, AI-Based Monitoring, Accelerometer and Gyroscope, Inertial Measurement Unit (IMU), Real-Time Alert System, Early Warning System, Seismic Activity Monitoring, Human feedback, Vibration Signal Denoising.

1. INTRODUCTION

There has been more construction, mining, and seismic activity in the past few years, which has increased the need for improved vibration detection and prediction systems. Conventional ground vibration monitoring techniques tend to depend on cumbersome, costly seismographs or outdated mechanical systems. These techniques are not sensitive or real-time enough for early warnings. This project offers a wiser, more affordable alternative: an AI-based vibration prediction system which employs accelerometers and gyroscopes contained in a six-axis IMU.

Using AI algorithms such as LSTM or Random Forest, we examine sensor readings to forecast future high-intensity vibrations and send real-time alerts. This two-sensing technique blends quantitative information from the IMU with qualitative observations, providing full vibration profiling on multiple axes. This system can alert individuals to potential issues in regions where there may be slight tremors or numerous human motions. Rather than observing only by hand or with simple warning systems, it applies machine learning to detect patterns. This combination of techniques catches subtle signs that larger vibrations are on the way, which is helpful both for keeping humans safe and designing cities.

This system isn't guesswork about what will happen; it's also being reliable regardless of what. Things such as what kind of ground, how buildings are constructed, and what is below can influence how vibrations behave. The traditional methods of discovering trouble aren't always accurate these days. This system relies on intelligent computers that help us learn, so it improves at detecting problems and validating warnings even when things get difficult.

The new project approach is user centered. It ensures that the platform remains straightforward to use for all, regardless of technical competence. The interface is simplified with easy-to-use visual dashboards and unambiguous alert notifications. This makes it easy for users to clearly grasp system outputs and make decisions based on valuable insights rather than be overwhelmed by complex technical information. The proposed solution also connects with current world-wide initiatives towards intelligent city development and sustainability. As cities grow, infrastructure faces new challenges such as continued construction, higher traffic vibrations, and external pressures. As cities grow, infrastructure faces new challenges like ongoing construction, increased vibrations from traffic, and environmental pressures. By using AI to monitor vibrations in urban areas, the system helps with better infrastructure planning, supports the protection of structural integrity, and promotes the goals of sustainable urban management.

2. LITERATURE REVIEW

Try and Gebhard highlighted the flexibility of IMU-based vibration monitoring beyond lab settings. Their work showed that small sensors could be integrated into wearable systems or attached to structures, enabling continuous activity tracking. The versatility of IMU sensors demonstrates their potential for broader use in civil and industrial applications where portability and cost matter [1]. Xie et al. applied Particle Swarm Optimization (PSO) to predict ground vibration velocity from long-hole blasting, showing the advantages of optimization algorithms over static models due to their adaptability to explosive force changes. This data-driven approach emphasizes the potential of combining AI techniques with sensor data to enhance prediction accuracy [2]. They also found that PSO-based models reduce computation compared to conventional iterative optimization, making them suitable for real-time applications such as construction blasting or seismic safety monitoring [2]. Ala et al. developed an Explainable AI (XAI)-based model for predicting and improving blast-induced ground vibrations in surface mining. The model's interpretability helped stakeholders understand the reasoning behind predictions, stressing the importance of transparency in AI monitoring systems used in critical environments [3]. Their study further enhanced XAI by allowing domain experts to adjust the model based on variable importance. This collaboration between human knowledge and machine intelligence increased model trustworthiness and practicality in real-world mining operations, ensuring responsible decision-making [3].

Firoozi and Firoozi conducted a systematic review of hybrid ML methods such as ensemble models and deep neural networks for predicting peak ground vibration. They highlighted the importance of feature engineering and signal preprocessing in handling accelerometer data, aligning with our real-time sensor data fusion approach [4]. A Springer review examined multiple AI and optimization techniques including Genetic Algorithms, Random Forests, and Gradient Boosting for ground vibration prediction, providing a foundation for our comparative model analysis [5].

In mining, researchers proposed a swarm-optimized deep neural network for forecasting blast-induced vibration intensity in open-pit mines. The model performed effectively on noisy datasets, showing its potential to handle accelerometer and gyroscope data in real-world settings [6]. Research using Relevance Vector Machines (RVMs) for predicting Peak Particle Velocity (PPV) in quarry blasting showed better performance with sparse data than Support Vector Machines, highlighting the need for models capable of handling limited data in vibration prediction systems [7].

Youwai and Pamungmoon used an explainable AI model to forecast pile-driving vibrations based on time-series IMU data, emphasizing the importance of preserving temporal features during preprocessing. This directly informs the structure of our vibration detection system using gyroscopes and accelerometers [8]. Teixeira et al. explored neural machine translation to convert seismic wave patterns into petrophysical models. Though focused on geology, their method offers a novel way to interpret ground vibrations as a "language," which could inform our research [9]. Finally, the Wiley review on sensor-integrated machine systems emphasized combining physical sensors with AI analytics for real-time industrial monitoring, supporting our goal of integrating human insights with quantitative IMU data [10].

3. PROPOSED METHEDOLOGY

Micro-electromechanical systems (MEMS) like the 6-axis Inertial Measurement Unit (IMU) combining an accelerometer and a gyroscope are vital for detecting abnormal vibrations in terrains, structures, and machinery. The accelerometer measures linear acceleration (e.g., shaking), while the gyroscope captures angular rotation (e.g., tilting). Undetected ground vibrations can signal structural failure or natural tremors. Traditional threshold-based systems often miss subtle patterns or raise false alarms. To address this, a machine learning model can analyze patterns, detect anomalies, and adapt using human-labeled data. The proposed system integrates sensor data, smart feature extraction, ML-based real-time classification, and a feedback loop for continuous improvement ensuring consistent detection and timely alerts.

Step-by-Step Methodology

1. Sensor Integration: The 6-axis IMU (MPU6050) measures acceleration (ax, ay, az) and rotation (gx, gy, gz), connected via I2C to a microcontroller (Arduino/Raspberry Pi) at 50–100 Hz sampling.

2. Data Collection: The IMU streams real-time motion data with timestamps, stored locally or sent to a server.

3. Signal Pre-processing: A low-pass Butterworth filter removes noise; mean and median filters reduce jitters. Features are extracted post-cleaning for fair model training.

4. Feature Extraction:

- Acceleration Magnitude: $A = \sqrt{(ax^2 + ay^2 + az^2)}$
- Gyroscope Magnitude: $G = \sqrt{(gx^2 + gy^2 + gz^2)}$
- Along with mean, max, std. dev., RMS, and dominant frequency (via FFT).

5. Data Labelling: Human experts label events as normal, moderate, or abnormal to create supervised datasets.

6. Model Training: Lightweight models like Random Forest or Decision Tree are trained and evaluated using accuracy, precision, and F1-score.

7. Alert Triggers (Threshold + AI):

Normal: $A < 0.3g$, $G < 50°/s$

Moderate: $0.3 \leq A \leq 0.6g$

Abnormal: $A > 0.6g$ or $G > 100°/s$

AI-driven predictions trigger alerts even if thresholds aren't met.

8. Alert System: Detected anomalies send notifications via Wi-Fi/Bluetooth to a dashboard/app with timestamp, location, and severity. On-site indicators (LED/Buzzer) also trigger.

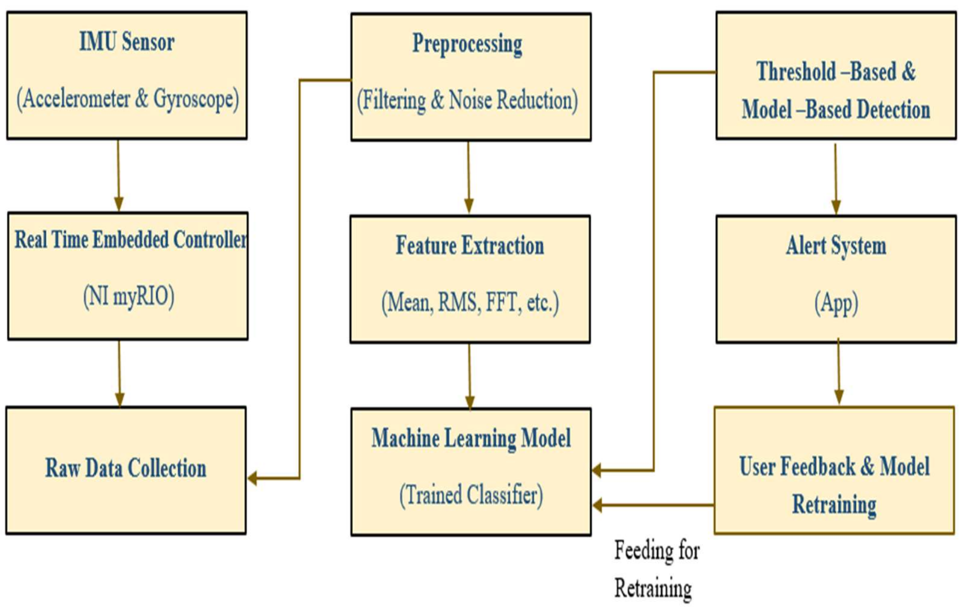
9. User Feedback & Retraining: Users can dismiss false alarms; this feedback retrains and refines the model for better accuracy.

10. Real-time Dashboard: Displays live acceleration/rotation plots and classification status (e.g., Green = Normal, Red = Alert) with logs for analysis.

11. Multi-Sensor Extension: Multiple IMUs across zones sync to a central server for faster collective decisions.

12. Scalability & Future Work: Applicable to bridges, mines, and earthquake zones. Long-term data can support forecasting using LSTMs or ConvNets for predictive insights.

4. Working Model of AI Powered Ground Vibration Prediction



1. Vibration Source: It is the source of vibrations itself-from construction activities, machinery, and traffic to natural tremors. It creates mechanical waves that travel into the ground or structures.

2. 6 Axis IMU sensor (Accelerometer + Gyroscope)

A 6-DOF (Degrees of Freedom) sensor capturing following:

- Linear acceleration (through accelerometer) in X, Y, and Z axes.
- Angular velocity (through gyroscope) in pitch, roll, and yaw.

Captures subtle to strong vibrations in real time. Physically connected to NI myRIO.

3. NI myRIO (Data Acquisition Unit) : Based on LabVIEW, the central controller in the system has the following responsibilities to execute for the final output of the result:

To gather raw sensor data through analog/digital I/O, Perform real-time processing and interface with software modules (through LabVIEW) Advantage: Compact, real-time, educational-grade hardware suitable for vibration monitoring

4. Signal Filtering and Pre-processing: Noise reduction using: Low-pass filters to eliminate high-frequency sensor noise. High-pass filters to ignore baseline drifts. Normalizes and smooths the raw vibration data for better ML input. To get the model prediction unbiased and on fair data so all the noise in the data get removed by feature extraction and filtering. So, the model gets the optimized decision output.

5. Feature Extraction: Meaningful features for classification and prediction are extracted: RMS: measures energy of vibration. FFT: Frequency domain conversion of a signal for identification of dominant vibration frequencies. Standard deviation: Measures variation of the signal and indicates severity of vibration. Kurtosis and Skewness: Detect impulsive or spiky vibrations are associated mostly with faults or abi-normal activity.

6. Machine Learning Classifier: The models Random Forest and LSTM are being used. They are trained with historical vibration data labelled as normal or not. Predicts: Whether incoming vibration is safe or critical, the source or severity according to the learned patterns.

7. Detection Threshold and Model: A dual alertness system: Threshold Logic: Simple if-then rules (for example, if RMS > .9, trigger alert), ML model output: The predicted output is used in defining risk levels. It incorporates the smarts of an AI model into its hard-coded safety buffers for solid detection.

8. Alert System: When vibration is dangerous: buzzer or LED is activated on myRIO, Optional: SMS/Email alert via LabVIEW web services or external GSM module. Alerts are instantaneous and local, with real-time processing by myRIO.

9. Data Logging and Model Retraining: A log is maintained for every vibration incidence (either passing or non-passing limits) and associated parameters. This recorded data is potentially beneficial for enhancing model accuracy over time and for collecting information about the vibration trend of the machine. Furthermore, the model can also be periodically retrained on these newly collected data to catch up with the changes in the evolution of the environment.

10. Feedback Loop: Data coming out of prediction/logging is used for retraining and fine-tuning the ML mode. Hence, the system tends to get smarter and more adaptive in course of time.

Table 1: COMPARATIVE ANALYSIS

Criteria	Existing Models	Proposed Model (Our System)
Objective	Basic seismic monitoring or scant vibration logging. Frequently does not include real-time alerting and ML.	Real-time abnormal vibration prediction and alerting with ML and myRIO.
Sensor Types	Primarily seismometers or isolated MEMS accelerometers.	6-axis IMU sensors (accelerometer + gyroscope) for precise 3D motion measurement.
Processing Hardware	Arduino, Raspberry Pi, or off-the-shelf seismographs.	NI myRIO real-time, FPGA-enabled hardware for accuracy and high-speed I/O.

Feature Extraction	Typically restricted to RMS or raw data recording. No in-depth analytics.	Advanced capabilities such as RMS, FFT, kurtosis, entropy, spectral centroid utilized for ML.
Machine Learning	Rarely exercised or employs traditional thresholds solely.	Classifies vibrations as safe or risky using SVM / LSTM / kNN.
Alert System	Threshold-based alarms or visual-only logs. No dynamic AI.	AI-driven alarms using RMS/FFT + ML output, displayed on UI or external device.
Real-Time Analysis	Delayed or post-event only.	Real-time prediction and alarming from live streaming sensor data.
Scalability	Requires manual expansion, no AI adaptability.	Can learn over time, get more accurate with more data collected.
Alert Trigger Range	Hard-coded thresholds (e.g., 1.5g acceleration).	Adaptive ML-based range; initial RMS alert ~0.8g–1.2g (customizable).
Power Efficiency	High power for seismographs or external GPUs.	Low power embedded myRIO board with high-efficiency processing.
Cost	Can be high due to specialized seismic equipment.	Cost-effective solution with standard IMU + myRIO + LabVIEW.
Accuracy	Moderate; tends to report after tremor.	High: Pre-shock pattern and frequency change detection using ML.

IMPLEMENTATION

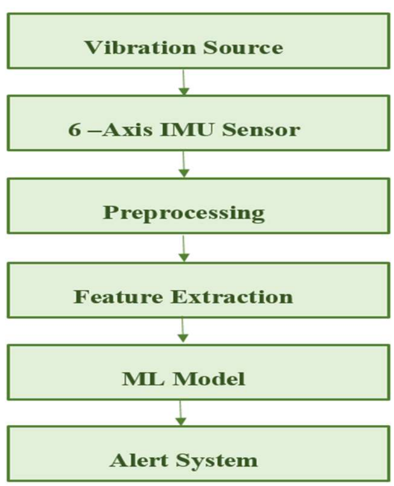


Fig (2): Flow Chart of Implementation of Model

1. Sensor Integration: A 6-axis inertial measurement unit consisting of a 3-dimensional accelerometer and a 3-dimensional gyroscope has been selected to capture linear as well as angular vibrations from the ground or structural surface.

2. Hardware Setup: The IMU has been mounted on the physical surface or structure selected for monitoring (for e.g. ground near construction/mining activities).

3. Connection with NI myRIO: The IMU communicates with NI-myRIO through SPI or I2C protocol.

4. Data acquisition: The NI myRIO allows for continuous data acquisition from the sensor without interruption at real-time sampling rates relevant for analyzing vibration signals either 100 Hz or higher.

5. Preprocessing in LabVIEW: After data cleansing, noise can be filtered away through digital filters like low-pass filters or moving-average filters.

6. Feature Extraction: LabVIEW estimates the following features from the real-time signal. RMS: Root Mean Square value signifies the power of the signal. FFT: Fast Fourier Transform refers to frequency components analysis. Standard deviation: It refers to the variation in signals. Signal Entropy Peak Acceleration: Measures sudden spikes in signal or randomness.

7. The machine learning model integration: A pre-trained classification model is integrated in LabVIEW (via DLL or embedded logic) and classifies the signal as such: Normal vibration Abnormal/ dangerous vibration

8. Dual Criteria Threshold Check: If the RMS value exceeds a chosen threshold (e.g., > 0.8g) OR if the ML model prediction is "abnormal", either event will trigger the alert.

9. Activation of Alert System: So in essence, once abnormal vibration is detected: Optional SMS/ Email alert can be sent via the modules connected.

10. Data Logging: All vibration data, predictions, and timestamps are stored locally for analysis and future training. It will also have user feedback data for qualitative observation therefore the better and optimized prediction will get.

11. User Interface (UI): Real-time waveform display (accelerometer/ gyroscope plots) Current status (normal/abnormal)

12. Alert logs and historical graph view: Real-Time Monitoring Loop. The system continuously monitors the environment in a loop for instant response to vibration events.

Alert Triggering Criteria

Condition	**Sensor Range Threshold (example)**	**Action**
Normal	Acceleration < 0.3g; Gyro < 50°/s	No alert
Moderate Vibration	Acceleration between 0.3g–0.6g	Log + Notify on app
Abnormal Vibration (Alert)	Acceleration > 0.6g; Gyro > 100°/s	Red Alert + Siren

The alert system operates on acceleration (linear) and gyroscope (angular) thresholds to classify vibrations as minor, moderate, or critical. This setup minimizes false alarms while ensuring fast responses to hazards. Under normal conditions (accel < 0.3g, gyro < 50°/s), no alert is triggered filtering background noise and mild motion to keep monitoring efficient. For moderate vibrations (0.3g–0.6g), the system logs data and sends early notifications to the connected app. This pre-alert phase improves real-time awareness and helps detect early signs of imbalance, machinery faults, or small tremors.

For critical vibrations (accel > 0.6g or gyro > 100°/s), the system triggers a red alert with siren and visual warnings. This high-priority response ensures immediate attention to risks like structural collapse, equipment failure, or seismic activity.

The tiered response design ensures precise classification with minimal false alerts by combining acceleration and angular thresholds. Alerts are sent promptly via SMS, email, push notifications, or integrated systems like sirens or display boards, ensuring redundancy even if one channel fails.

Each alert includes:

- Location of abnormal vibration/activity
- Severity level (low, medium, or critical)
- Identified cause (if available)
- Safety instructions or action steps (e.g., evacuation, inspection).

Alerts are categorized by severity critical alerts go directly to emergency services, while minor ones are logged for review. All alerts are stored for analysis to improve model accuracy and validate true or false events.

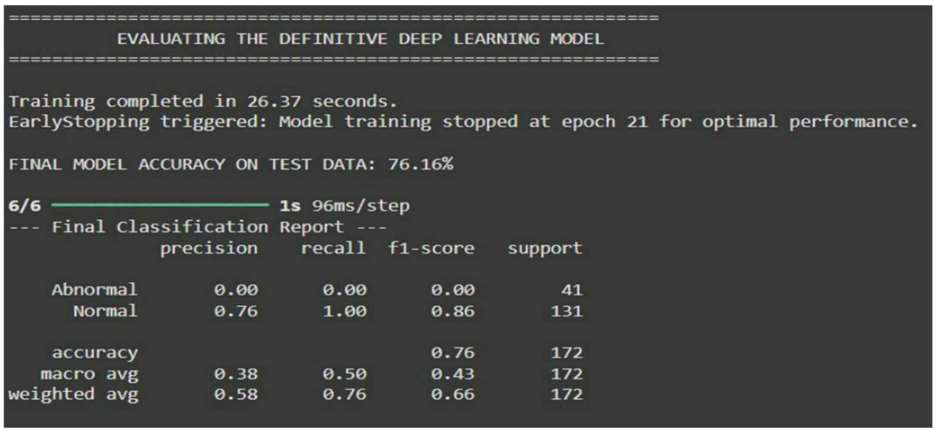
Thus, the alert system bridges detection and human response, ensuring timely, accurate, and actionable information to mitigate vibration-related risks.

Table 2: Analysis of Sensor

Criteria	**Single-Sensor (Accelerometer Only)**	**Multi-Sensor (Accelerometer + Gyroscope)**
Type of motion captured	Captures only linear acceleration, limiting vibration analysis.	Captures both linear and angular motion, giving a complete profile.
Measurement axes	Provides three-axis measurement that may miss complex patterns.	Extends to six degrees of freedom, offering richer vibration data.
Rotational detection	Fails to detect rotational disturbances effectively.	Detects even minor rotational vibrations through gyroscopes.
Noise handling	Struggles with filtering environmental noise.	Combines sensor data to improve noise filtering.
Accuracy in noisy settings	More prone to false positives from external interference.	Cross-verification across sensors reduces false positives.
System reliability	Easy to implement but less reliable in dynamic environments.	Performs well under dynamic conditions with better robustness.
Long-term stability	Monitoring accuracy may drop due to sensor drift.	Maintains stability by balancing accelerometer and gyroscope data.
Sensitivity to microtremors	May not detect subtle precursors of large vibrations.	Detects small-scale tremors using combined sensing.
Predictive potential	Limited awareness restricts predictive modeling accuracy.	Enables stronger predictive modeling with diverse data.
Overall effectiveness	Simpler but inadequate for advanced prediction.	More complex but ensures higher accuracy and reliability.
Noise handling	Struggles with filtering environmental noise.	Combines sensor data to improve noise filtering.

Vibration detail	Gives only basic intensity readings without direction.	Provides detailed vibration profiles including direction and intensity.
Accuracy in noisy settings	More prone to false positives from external interference.	Cross-verification across sensors reduces false positives.
System reliability	Easy to implement but less reliable in dynamic environments.	Performs well under dynamic conditions with better robustness.

RESULT:



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============================================================
          EVALUATING THE DEFINITIVE DEEP LEARNING MODEL
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Training completed in 26.37 seconds.
EarlyStopping triggered: Model training stopped at epoch 21 for optimal performance.

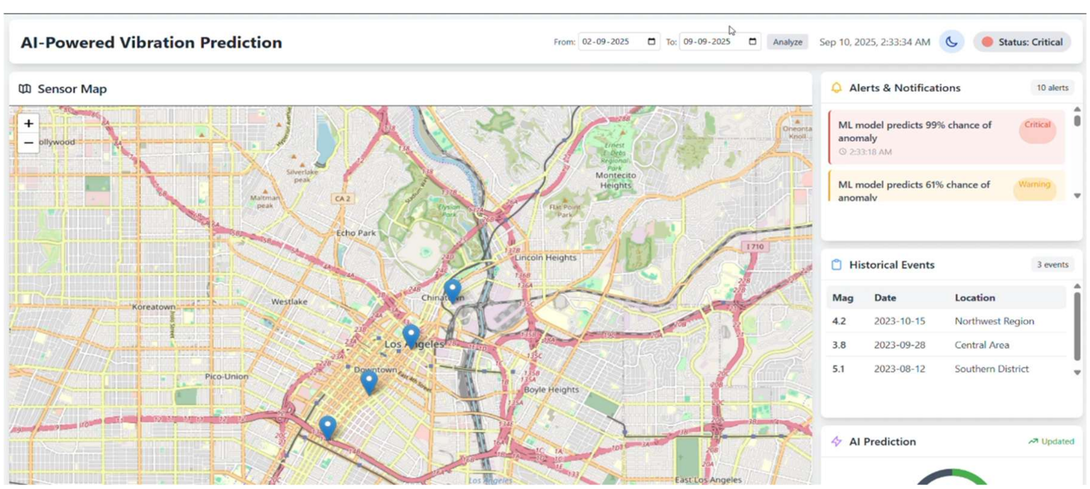
FINAL MODEL ACCURACY ON TEST DATA: 76.16%

6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 96ms/step
--- Final Classification Report ---
              precision    recall  f1-score   support

    Abnormal       0.00      0.00      0.00        41
      Normal       0.76      1.00      0.86       131

    accuracy                           0.76       172
   macro avg       0.38      0.50      0.43       172
weighted avg       0.58      0.76      0.66       172
```

The evaluation result of the final deep learning modelof above, which produced the test accuracy of 76.16%. The training halted prematurely in epoch 21 so that the model would not experience overfitting and provide optimal results. The classification report indicates that normal cases are highly classified well by the model as it gets perfect recall (1.00) and a robust F1-score (0.86). This makes it very near to the fact that almost all normal instances are classified well. However, the abnormal cases performed badly since both precision and recall dropped to 0.00, indicating total misclassification of that class. Finally, the weighted average F1 score of 0.66 shows imbalance, indicating that while the model is reliable for normal prediction, considerable optimization has to be done to enhance its performance in abnormal event detection, thus leading to a more balanced performance over classes.



The above dashboard which is part of the AI-based ground vibration prediction system used to monitor seismic activity through the use of sensor data and AI modeling. The image shows a map with multiple sensor locations in green, yellow, and orange to depict status levels. Display on run time, besides, angular values and velocity sensor readings with one of them flagged as something more critical than the others are. On this dashboard, there is a time-series line chart showing acceleration changes with threshold indicators for further monitoring values in the back. The right panel of the system shows alerts, historical seismic events with their magnitudes and dates, and an AI model prediction with a 30% chance of a tremor in the next 30 minutes. Thus, the dashboard combines real-time ground vibrations monitoring and historical analysis with predictive modeling, allowing early warning and situation awareness. The layered architecture of the system guarantees the detection of sensor anomalies and their validation with historical data to reduce false alarm rates. The integration of qualitative observations and quantitative sensor inputs in the dashboard illustrates the strong AI application in seismic risk management.

LIMITATIONS

The proposed AI-based ground vibration prediction system, combining qualitative and quantitative observations, shows strong potential but faces several limitations that must be addressed for greater reliability, scalability, and adaptability in real-world use. Sensor Dependency & Accuracy: System performance depends heavily on the type, number, and calibration of sensors. Insufficient or faulty sensors can cause data loss or inaccurate readings.
Qualitative Observation Variability: Human observations are subjective and can vary across individuals, climates, or social contexts, leading to inconsistencies in the training data. Limited Environmental Scope: Experiments so far have been conducted in controlled or semi-controlled settings, limiting model applicability to diverse terrains, extreme weather, or unique geological conditions. Data Volume & Quality: The dataset is small and lacks long-term continuous monitoring, preventing the model from learning temporal vibration patterns. Computational Complexity: Deep learning models require high computational resources, making real-time deployment on low-power or edge devices difficult. Integration Challenges: Merging quantitative sensor data with qualitative human reports needs robust data fusion methods. The current system's basic fusion mechanism may miss deeper correlations. Prediction Uncertainty: The model does not yet provide confidence intervals or uncertainty estimates, which are essential for risk-sensitive environments where small prediction errors could have serious consequences. Scalability Issues: The system works in pilot setups but may struggle at large scale due to high infrastructure costs, sensor maintenance needs, and the massive heterogeneous data inflow from widespread networks.

5. CONCLUSION

The proposed AI-based ground vibration prediction system demonstrates a promising step toward integrating both quantitative sensor data and qualitative human observations for accurate and intelligent vibration monitoring. By leveraging accelerometer and gyroscope measurements along with AI-driven analytics, the system provides a more adaptive, data-informed approach compared to traditional threshold-based methods. However, despite its effectiveness in controlled environments, the system's current limitations including sensor dependency, subjective variability in human inputs, limited environmental validation, and scalability issues highlight the need for further refinement. Expanding the dataset with long-term, real-world monitoring across varied terrains will help the model learn more complex temporal patterns and enhance its robustness. Additionally, improving data fusion techniques for integrating heterogeneous data sources and incorporating uncertainty estimation will strengthen the model's reliability in safety-critical applications.

In future development, emphasis should be placed on lightweight model optimization for deployment on edge or IoT devices, enabling real-time monitoring in remote or resource-constrained locations. Establishing standardized calibration protocols, automated retraining pipelines, and cloud-based analytics dashboards can further improve operational scalability.

Overall, while the system represents a significant innovation in vibration detection and risk prediction, continuous research, large-scale validation, and the inclusion of explainable AI methods are essential to make it a practical, trustworthy, and industry-ready solution for applications in mining, construction, and seismic safety monitoring.

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