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Design and Development of an IoT-Based Ground Vibration Monitoring System with Landslide Potential Classification Using SVM

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Abstract

Landslides are natural disasters that can cause casualties, environmental damage, and infrastructure losses. One challenge in landslide mitigation is the limited availability of monitoring systems that can provide fast, real-time, and interpretable information about ground conditions. This study aims to design and develop an Internet of Things (IoT)-based ground vibration monitoring system with landslide potential classification using Support Vector Machine (SVM). The system uses an MPU6050 sensor to acquire ground vibration data and an ESP8266 microcontroller to transmit data through a Wi-Fi network to a server. The collected data are processed through preprocessing, windowing, feature extraction, and standardization before being classified into three condition categories: Safe, Alert, and Danger. The classification results are displayed on an LCD, visualized through a web dashboard, and used to activate a relay as a warning mechanism when a dangerous condition is detected. The testing results show reliable data transmission with a 100% delivery success rate in the observed test and an average latency of approximately 0.3 seconds. The SVM model achieved 99.79% accuracy, with high precision, recall, and F1-score for all classes. Therefore, the proposed prototype can support ground vibration monitoring and early landslide warning efforts more effectively.

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1. Introduction

Landslides are among the most serious geological disasters because they may occur suddenly and cause human casualties, damage to infrastructure, environmental degradation, and economic losses. The risk becomes higher in hilly or mountainous areas where the slope is steep, the soil structure is unstable, and rainfall or human activity can accelerate changes in slope stability. In many cases, communities and managers of vulnerable areas do not receive sufficient early information about changes in ground conditions. This situation makes mitigation difficult because the potential danger is often recognized only after visible cracks, ground movement, or other warning signs have already appeared.

Traditional monitoring activities usually depend on direct inspection, manual measurement, or periodic observation. Although such activities are useful, they have several limitations. Manual observation requires access to the monitoring site, cannot always be performed continuously, and may be ineffective when the location is difficult to reach. In addition, manual observation does not always provide real-time data. For areas with potential landslide risk, a more responsive system is needed so that changes in ground conditions can be recorded, transmitted, analyzed, and presented to users quickly.

Internet of Things (IoT) technology provides a suitable approach for this problem because it enables sensors, microcontrollers, networks, and servers to communicate automatically. Through IoT, a monitoring device can be installed in a field location, acquire physical data, transmit the data through a wireless connection, and display the result through a dashboard. This architecture allows users to observe conditions remotely without having to be physically present at the monitored site. In the context of landslide monitoring, IoT can support continuous observation and provide a foundation for early warning systems. Similar IoT and wireless sensor network approaches have been discussed for landslide monitoring and early warning applications (Ragnoli et al., 2023; Wang et al., 2022).

Ground vibration is one of the physical indicators that can be monitored to detect dynamic changes in soil or slope conditions. Vibration data can be acquired using an inertial sensor such as MPU6050, which contains an accelerometer and gyroscope. In this study, the acceleration data on the x, y, and z axes are used to represent vibration patterns. However, raw sensor data cannot be directly interpreted by users because the readings are numerical, dynamic, and may contain noise. Therefore, the data must be processed into more meaningful information.

Many early monitoring systems use simple threshold rules to determine whether a condition is safe or dangerous. Threshold-based decision-making is easy to implement, but it may not be sufficiently adaptive when data fluctuate or are affected by noise. Machine learning offers an alternative because it can learn patterns from data and classify new inputs based on the learned characteristics. Support Vector Machine (SVM) is one of the algorithms that can be used for classification because it creates an optimal separating boundary among classes. In this study, SVM is used to classify ground vibration conditions into Safe, Alert, and Danger categories. Machine learning studies also indicate that SVM remains relevant for landslide-related classification and susceptibility assessment (Fang et al., 2022; Tehrani et al., 2022).

The contribution of this study is the development of a prototype that integrates ground vibration acquisition, IoT-based data transmission, preprocessing and feature extraction, SVM classification, local display, web dashboard visualization, and relay-based warning output. The system is expected to transform raw vibration readings into operational information that can be understood more easily by users and can support landslide mitigation efforts.

2. Research Methodolgy

This study uses a Research and Development (R&D) method because the main objective is to design, build, and evaluate a working prototype. The research does not only analyze data but also produces an integrated system consisting of hardware, software, and a machine learning model. The main research stages include literature study, system design, hardware assembly, software development, data acquisition, preprocessing, feature extraction, SVM training, testing, and evaluation.

The literature study was conducted to understand landslide monitoring, ground vibration measurement, IoT architecture, MPU6050 sensor characteristics, ESP8266 communication capability, web-based monitoring, and SVM classification. The system was then designed by determining the required components and the workflow of data from sensor acquisition to user output. After the design stage, the prototype was assembled and programmed. The collected vibration data were then labeled according to the designed condition scenarios and processed into features for machine learning.

2.1 Hardware and Software Design

The hardware design consists of an ESP8266 NodeMCU, an MPU6050 sensor, a 16x2 I2C LCD, a relay module, a buck converter, power supply, jumper cables, and a Wi-Fi or hotspot connection. The ESP8266 acts as the main controller and communication module. It reads sensor values, manages Wi-Fi connection, and sends data to the server. The MPU6050 acts as the main sensing unit and records acceleration on the x, y, and z axes. The LCD provides local information, while the relay activates a warning device such as a buzzer or lamp when the classification result indicates a dangerous condition. The use of ESP8266 and MPU6050 is consistent with previous IoT-based landslide detection prototypes (Mega Utama, 2022).

The software side includes the embedded program for the ESP8266, server-side processing, database storage, SVM model, and web dashboard. The embedded program initializes the sensor and output devices, connects the system to Wi-Fi, reads sensor data at a certain interval, and sends data to the server. The server receives incoming data, stores it with a timestamp, processes the data, loads the trained SVM model, performs classification, and updates the dashboard. This design ensures that the system does not only measure vibration but also converts it into condition information.

2.2 System Workflow

The workflow starts when the device is powered on. The ESP8266 initializes the MPU6050 sensor, LCD, and relay. After initialization, the device checks Wi-Fi connectivity. If the network is not available, the device retries the connection until it succeeds. Once connected, the system reads ground vibration data from the MPU6050. The raw readings are transmitted to the server and can also be processed into vibration indicators before classification.

On the server side, the incoming data are stored in a database to support historical monitoring and evaluation. The data are processed through windowing, where several readings are grouped into a time segment. The purpose of windowing is to make each sample more representative and less sensitive to momentary noise. Feature extraction is then performed so that the SVM model receives compact and informative inputs rather than raw sequential readings. After classification, the result is returned to the output layer. Safe and Alert conditions are displayed on the LCD and dashboard, while the Danger condition also triggers the relay.

2.3 Data Acquisition and Feature Extraction

Data acquisition was performed using the MPU6050 sensor. The primary sensor outputs are acceleration values on the x, y, and z axes. From these values, the acceleration magnitude and dynamic vibration indicators can be calculated. The data were collected under three condition scenarios: Safe, Alert, and Danger. Safe represents low and relatively stable vibration, Alert represents moderate vibration or an increasing pattern, and Danger represents higher vibration intensity that requires warning output. The MPU6050 sensor specification supports multi-axis acceleration readings suitable for vibration-related measurements (MPU-6000 and MPU-6050 Product Specification, 2013).

Before classification, the data undergo preprocessing. This stage is required because vibration readings may contain noise and can fluctuate depending on environmental disturbances. The readings are grouped using windowing to represent short time intervals. From each window, statistical features are extracted, including mean, standard deviation, variance, root mean square (RMS), peak value, and acceleration magnitude. These features are selected because they can describe the average level, spread, energy, and maximum vibration intensity in a time segment. Feature standardization is also applied because SVM is sensitive to differences in feature scale.

2.4 SVM Classification and Evaluation

Support Vector Machine is used to classify the extracted features into three output classes: Safe, Alert, and Danger. The SVM algorithm attempts to find a separating hyperplane that maximizes the margin between classes. When the classes are not linearly separable, a kernel such as radial basis function (RBF) can be used to map data into a higher-dimensional feature space. The SVM model is trained using labeled vibration data and then tested using data that are not used during training.

The evaluation metrics used in this study are accuracy, precision, recall, F1-score, and confusion matrix. Accuracy measures the proportion of total correct predictions. Precision measures the correctness of predictions for a specific class, while recall measures the ability of the model to identify all actual samples of a class. F1-score provides a balanced measure between precision and recall. The confusion matrix is used to observe which classes are classified correctly and which classes are misclassified

3. Results and Discussion

The prototype was successfully implemented as an integrated IoT monitoring system. The hardware components were connected according to their functions, and the software system was able to receive, store, process, classify, and visualize sensor data. The ESP8266 functioned as the main controller, the MPU6050 sensor provided ground vibration readings, the LCD displayed local status, and the relay acted as a warning actuator. The web dashboard provided remote visualization of the monitoring results.

The implementation shows that the proposed system is not limited to sensor reading. It includes a complete data flow from sensing to decision output. This is important because a monitoring device that only displays sensor values may be difficult for users to interpret. By adding machine learning classification, the system can translate numerical readings into condition labels that are easier to understand and act upon.

3.1 Hardware Implementation

The hardware testing confirmed that the main components could operate together. The ESP8266 successfully managed sensor reading and network communication. The MPU6050 sensor responded to changes in vibration intensity, while the LCD displayed the system status. The relay was controlled by the system logic and could be used to activate a warning device. The use of a buck converter helped stabilize the power supply so the circuit could operate more reliably during testing.

The prototype arrangement also makes the system flexible for further development. Because the system is based on modular components, additional sensors such as soil moisture, rainfall, or slope inclination sensors can be integrated in future research. Such integration would make the classification more comprehensive because landslide potential is influenced by more than one physical parameter.

3.2 Sensor Testing

Sensor testing was conducted to determine whether the MPU6050 could represent different vibration conditions. In the Safe condition, the dynamic vibration value was generally low and stable. In the Alert condition, the value increased and showed a moderate pattern. In the Danger condition, the reading became higher and more fluctuating. These observations indicate that vibration intensity can be differentiated numerically and can be used as a classification input.

The pattern observed in sensor testing supports the selection of MPU6050 as the main vibration sensor in the prototype. Although the sensor is relatively inexpensive and widely used in embedded systems, it can provide acceleration readings that are sufficient for prototype-scale monitoring. However, field implementation would require careful calibration, protective casing, stable installation, and additional validation under longer observation periods.

3.3 Wi-Fi and Data Transmission Testing

The system was tested for Wi-Fi connectivity and data transmission. The observed initial connection time was approximately 3 seconds. During the test, 17 data records were successfully transmitted to the server, with 0 failed transmissions. The delivery success rate was 100%, and the average transmission latency was approximately 0.3 seconds. These values indicate that the communication process worked reliably during the observed testing session.

Low latency is important in an IoT monitoring system because the user needs near real-time information. A delay that is too long may reduce the usefulness of the warning output. In this prototype, the observed latency is acceptable for monitoring and dashboard update purposes. Nevertheless, larger-scale field deployment should test the system under different network conditions because Wi-Fi signal quality, distance from access point, weather, and power stability can affect data transmission performance.

3.4 Classification Performance

The SVM model produced a strong classification result. The overall accuracy reached 99.79%. The Safe class achieved 100% precision, 100% recall, and 100% F1-score. The Alert class achieved 99% precision, 100% recall, and 99% F1-score. The Danger class achieved 100% precision, 97% recall, and 99% F1-score. These results indicate that the extracted vibration features contain patterns that can be learned effectively by SVM.

The high recall of Safe and Alert classes shows that the model can identify normal and transitional conditions very well. The Danger class achieved perfect precision but slightly lower recall. This means that when the model predicts Danger, the prediction is highly reliable, but a small number of actual Danger samples may still be classified as another class. In an early warning context, this aspect should be considered carefully because missing a dangerous condition may have more serious consequences than producing a false alarm. Future work should increase the number and variation of Danger samples to improve recall.

3.5 Dashboard Monitoring

The dashboard provides a remote interface for observing monitoring results. The displayed information includes sensor readings, timestamps, classification status, historical data, and graphical visualization. This makes the dashboard useful not only for real-time observation but also for reviewing past data. Through the dashboard, users can observe whether the condition remains Safe, moves to Alert, or reaches Danger status.

The dashboard also increases the usability of the system because the user does not need to interpret raw numerical data manually. The classification label provides a direct indication of the current condition. This supports the practical objective of the system, which is to present clear and understandable information. The combination of local LCD output and web dashboard output also makes the system more flexible because information can be viewed both near the device and from a remote location.

3.6 Comparative Discussion and Limitations

Compared with a threshold-based monitoring system, the proposed SVM-based approach provides a more adaptive decision mechanism. Threshold rules are simple and easy to implement, but they depend heavily on fixed limits. If vibration data fluctuate because of noise, external disturbances, or changes in installation conditions, a fixed threshold may lead to false alarms or missed detections. By using feature extraction and machine learning, the system can classify based on patterns rather than a single instantaneous value. This limitation is important because vibration-based monitoring is affected by environmental noise and requires careful interpretation (Le Breton et al., 2021; Maresca et al., 2022).

Despite its promising results, the system still has limitations. First, the main parameter is ground vibration, while landslide potential is also affected by rainfall, soil moisture, slope geometry, vegetation, and geological structure. Second, the prototype still requires broader field testing with longer observation periods. Third, the dataset needs to be expanded to increase the ability of the model to generalize to different field conditions. Fourth, the device enclosure and power supply should be improved before practical outdoor deployment. These limitations do not reduce the contribution of the prototype, but they indicate directions for further development.

3.7 Practical Implications

The results indicate that an IoT-based monitoring prototype can be used as an accessible platform for observing ground vibration conditions in landslide-prone areas. The main practical value of the system is the ability to provide condition labels instead of only numerical sensor values. For non-technical users, labels such as Safe, Alert, and Danger are easier to understand and can support faster situational awareness. The combination of LCD, relay, and web dashboard also provides multiple layers of communication. The LCD is useful for local inspection, the relay supports immediate warning output, and the dashboard supports remote observation and documentation.

The use of ESP8266 and MPU6050 also shows that a low-cost prototype can be developed using commonly available components. This is important for early-stage research because the system can be reproduced, modified, and expanded without requiring expensive instrumentation. In a practical deployment scenario, several sensor nodes could be placed at different points of a slope and connected to a central dashboard. Such a multi-node architecture would provide a broader picture of vibration distribution and improve the usefulness of the monitoring system.

Nevertheless, the system should be interpreted as a prototype rather than a complete official early warning system. A complete system would require calibration against geotechnical measurements, environmental sensors, validated field thresholds, reliable power supply, protective enclosure, communication redundancy, and operational procedures for warning dissemination. Therefore, the contribution of this research is primarily to demonstrate the feasibility of integrating IoT sensing and SVM classification for landslide potential monitoring.

3.8 Reliability Considerations

Reliability is a crucial issue in monitoring systems because incorrect readings, communication loss, or unstable power supply can affect the decision output. In the observed test, the data transmission result was satisfactory, but broader testing is still necessary. A longer experiment should evaluate system performance during different weather conditions, different Wi-Fi signal strengths, and different vibration sources. The system should also be tested with continuous operation to determine whether the sensor readings drift over time and whether the server can handle larger volumes of incoming data.

Another reliability issue is the classification of Danger conditions. Although the model achieved high overall performance, the recall of the Danger class was lower than the recall of Safe and Alert classes. In safety-related applications, false negatives should be minimized. Future dataset development should therefore include more samples from dangerous or high-vibration conditions. Class balancing, additional feature extraction, model comparison, and conservative decision rules may also be considered to reduce the risk of missed danger detection.

The dashboard and database are also important for reliability evaluation because historical data allow researchers to review system behavior after testing. By comparing the timestamp, vibration values, classification status, and relay output, the consistency of the entire data flow can be evaluated. This historical record can also support future model retraining when new field data are collected.

4. Conclusion

This study successfully designed and developed an IoT-based ground vibration monitoring system with landslide potential classification using Support Vector Machine. The system uses an MPU6050 sensor to acquire vibration data and an ESP8266 microcontroller to transmit the data through Wi-Fi to a server. The data are processed through preprocessing, windowing, feature extraction, and standardization before classification. The output classes are Safe, Alert, and Danger. The testing results show that the system can perform real-time monitoring, transmit data to the server, display results on an LCD, update a web dashboard, and activate a relay as a simple warning mechanism. The SVM model achieved 99.79% accuracy, with high precision, recall, and F1-score for each class. These findings indicate that the proposed prototype can support ground vibration monitoring and provide early warning information for landslide potential. Future research should add other environmental parameters such as soil moisture, rainfall, and slope inclination. The dataset should be expanded with more diverse field conditions, and the system should be tested for longer periods in actual landslide-prone areas. Future studies may also compare SVM with other algorithms such as Random Forest, XGBoost, or neural networks to determine the most suitable model for vibration-based landslide monitoring.

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