

**MACHINE LEARNING-BASED GROUND MOTION
PREDICTION MODELS FOR WEST JAVA, INDONESIA**

BY

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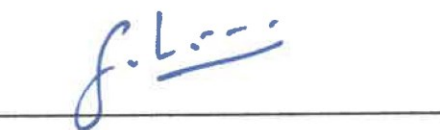
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I dedicate this to my beloved country, Indonesia.

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LIST OF ABBREVIATIONS

EEWS	: Earthquake Early Warning System
GMPM	: Ground Motion Prediction Model
PGA	: Peak Ground Acceleration
PGV	: Peak Ground Velocity
PGD	: Peak Ground Displacement
CB	: Categorical Boosting
GB	: Gradient Boosting
RF	: Random Forest

ABSTRACT

Full Name : Andy Rachmadan

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Indonesia, one of the most earthquake-prone countries in the world, is currently developing an Earthquake Early Warning (EEW) system. A key component of this system, the Regional EEW, relies on Ground Motion Prediction models (GMPMs) to issue end-user alerts. However, in West Java, one of the pilot regions for this project, there is a lack of region-specific GMPMs essential for accurate early warnings. Traditionally, GMPMs are developed using linear regression based on complex, predefined mathematical equations and coefficients. However, Machine learning offers the advantages of bypassing the need for predefined equations and effectively capturing the nonlinear behavior present in ground motion data. To address this gap, we evaluated three machine learning algorithms (i.e. Categorical Boosting [CB], Gradient Boosting [GB], and Random Forest [RF]) to develop GMPMs for three tectonic categories: Shallow-crustal, Interface, and Intralab. These models were used to predict Peak Ground Acceleration (PGA) in West Java, utilizing 3561 strong ground motion records from 383 earthquakes with moment magnitude ranging from 2.4 to 7 and epicentral distance between 5.5 to 867 km, recorded since 2010. Our results show that The Categorical Boosting model outperformed the others across all three tectonic categories, with the lowest Mean Squared Error values (0.72, 0.48, 0.69), and Standard

Deviation of Residuals (0.85, 0.69, 0.83), as well as the highest Pearson correlation coefficient-value (0.86, 0.90, 0.91) and Coefficient of Determination (0.75, 0.81, 0.82) for Shallow-crustal, Interface, and Intraslab events, respectively, demonstrating strong accuracy in predicting PGA. The model was further validated with recent earthquake data and from 2024 showing good agreement and confirming its robustness. Epicentral Distance and Moment Magnitude were the most influential in predicting PGA among the six explanatory variables used in this study. These findings highlight the potential of machine learning models to improve the accuracy of ground-shaking predictions, contributing to Indonesia's Earthquake Early Warning System (EEWS) success.

Keywords: Ground Motion Prediction, Earthquake, Machine Learning, Indonesia's Earthquake Early Warning System

ملخص الرسالة

الاسم الكامل : أندي رحمدان

عنوان الأطروحة : نموذج تنبؤ حركة الأرض القائم على التعلم الآلي لغرب جاوة، إندونيسيا

المجال الرئيسي : الجيوفيزياء

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إندونيسيا، واحدة من أكثر الدول عرضة للزلازل في العالم، تعمل حاليًا على تطوير نظام الإنذار المبكر للزلازل (EEW). يعتمد أحد المكونات الرئيسية لهذا النظام، وهو نظام الإنذار المبكر الإقليمي (Regional EEW)، على نماذج التنبؤ بحركة الأرض (GMPMs) لإصدار تنبيهات للمستخدمين النهائيين. ومع ذلك، في جاوة الغربية، وهي إحدى المناطق التجريبية لهذا المشروع، هناك نقص في نماذج GMPMs الخاصة بالمنطقة، وهي ضرورية للتحذيرات المبكرة الدقيقة. تقليديًا، تُطوّر نماذج GMPMs باستخدام الانحدار الخطي المستند إلى معادلات رياضية معقدة وقيم معاملات محددة مسبقًا. ولكن التعلم الآلي يوفر ميزة تجاوز الحاجة إلى معادلات محددة مسبقًا، والقدرة على التقاط السلوك غير الخطي الموجود في بيانات حركة الأرض بشكل فعال.

لمعالجة هذه الفجوة، قمنا بتقييم ثلاثة خوارزميات تعلم آلي: التعزيز التصنيفي (Categorical Boosting - CB)، التعزيز التدريجي (Gradient Boosting - GB)، والغابات العشوائية (Random Forest - RF)، لتطوير نماذج GMPMs لثلاث فئات تكتونية: الزلازل القشرية الضحلة (Shallow-crustal)، وزلازل الحدود التكتونية (Interface)، والزلازل داخل اللوح التكتوني. (Intraslab) استخدمت هذه النماذج للتنبؤ بالتسارع الأقصى للأرض (PGA) في جاوة الغربية، باستخدام ٣٥٦١ تسجيلًا قويًا لحركة الأرض من ٣٦٥ زلزالًا تتراوح قوتها بين ٢,٤ و ٧,٠ وبمسافات بين المركز السطحي للزلازل ونقاط القياس بين ٥,٥ و ٨٦٧ كم، مسجلة منذ عام ٢٠١٠.

أظهرت النتائج أن نموذج التعزيز التصنيفي (Categorical Boosting) تفوق على النماذج الأخرى في جميع الفئات التكتونية الثلاث، حيث حقق أدنى قيم لمتوسط الخطأ التريبيعي (٠,٧٢, ٠,٤٨, ٠,٦٩)، وأدنى انحراف معياري للبواقي (٠,٨٥, ٠,٦٩, ٠,٨٣)، وأعلى معامل ارتباط بيرسون (٠,٨٦, ٠,٩٠, ٠,٩١)، وأعلى معامل تحديد (٠,٧٥, ٠,٨١, ٠,٨٢) لفئات الزلازل القشرية الضحلة، والحدودية، وداخل اللوح التكتوني على التوالي، مما يدل على دقة قوية في التنبؤ بـ PGA.

تم التحقق من صحة النموذج باستخدام بيانات زلازل حديثة من عام ٢٠٢٤، وأظهرت النتائج توافقًا جيدًا مما أكد متانته. وكانت المسافة بين المركز السطحي للزلازل وحجمه الزلزالي من أكثر العوامل تأثيرًا في التنبؤ بـ PGA من بين ستة متغيرات تفسيرية استخدمت في هذه الدراسة. تسلط هذه النتائج الضوء على إمكانات نماذج التعلم الآلي في تحسين دقة التنبؤ بهزات الأرض، مما يساهم في نجاح نظام الإنذار المبكر للزلازل في إندونيسيا.

الكلمات المفتاحية: تنبؤ حركة الأرض، زلازل، تعلم آلي، نظام الإنذار المبكر للزلازل في إندونيسيا

CHAPTER 1

INTRODUCTION

1.1 Background

Earthquakes present significant hazards, leading to widespread destruction, and loss of life. Thus, areas with high seismic activity require robust systems or technologies to mitigate these disasters and minimize casualties. The Earthquake Early Warning System (EEWS) stands out as a crucial life-saving tool designed to meet this challenge (Mittal et al., 2022). By 2020, EEWS has been implemented in nine countries, with testing underway in thirteen more (Cremen and Galasso, 2020; Dallo et al., 2022). EEWS has already provided helpful public alerts during several major earthquakes (Allen and Melgar, 2019; Meier, 2017).

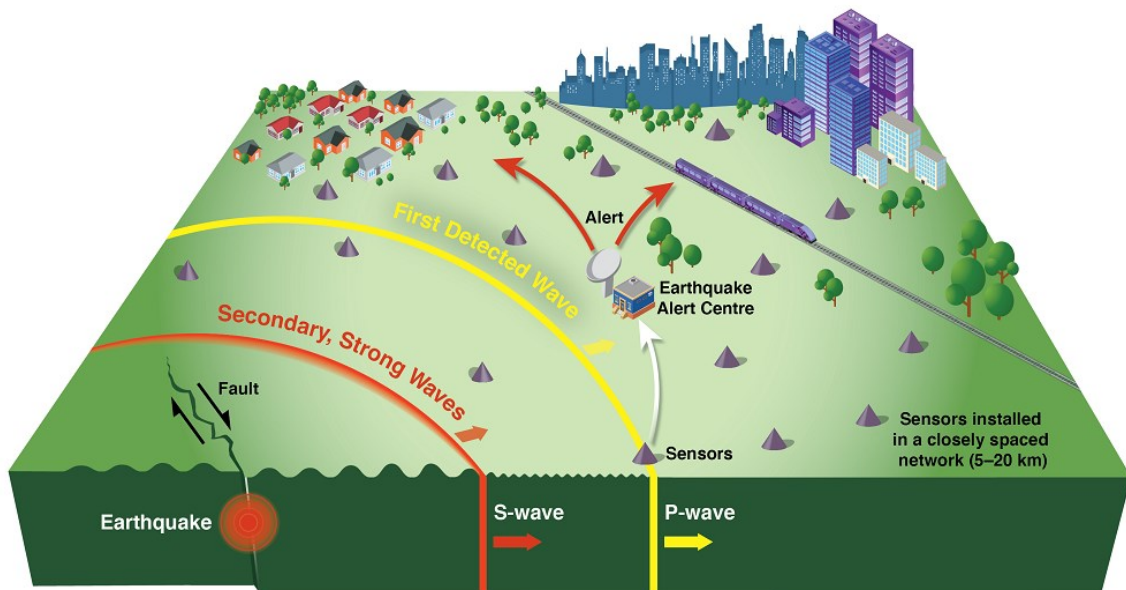


Figure 1. Principles of an EEWS (<https://www.earthquakescanada.nrcan.gc.ca/>)

During an earthquake, the rupture of a fault generates two types of waves: body waves (P-waves and S-waves) and surface waves. The first to be detected by seismometers are the primary P-waves, which travel at the highest velocity (6-7 km/s). In contrast, the slower-traveling S-waves and surface waves cause the most surface damage due to their perpendicular particle motion to the wave propagation direction, with surface waves transmitting most of the seismic energy (Bormann et al., 2012). The EEWS leverages the time difference between the arrival of P-waves and S-waves to issue alerts to end users (Katayama and Horiuchi, 2015; Tajima and Hayashida, 2018).

EEWS is designed to provide alerts to end users within seconds, up to ten seconds, before destructive waves reach a particular area (Y. Liu et al., 2024). Despite their brevity, these alerts can be utilized across various sectors to reduce the impact of earthquakes. Automatic actions such as shutting down nuclear power plants, closing gas pipelines to prevent fires, stopping elevators and opening their doors, and slowing down high-speed trains can be triggered. Meanwhile, individuals receiving the alerts can take actions such as dropping, covering, and holding on, or if time permits, moving to a safer location inside buildings or evacuating to avoid injury or fatalities (Chatterjee et al., 2022; Satriano et al., 2011).

Currently, there exist two approaches within this system: on-site EEWS and regional EEWS. Both approaches yield outputs such as ground shaking estimations and countdowns for early earthquake warnings tailored to each end user's region. The on-site EEWS deploys single or multiple sensors directly at the target site (Zollo et al., 2014). This system predicts ground shaking from S waves by analyzing data from P waves detected by sensors in the target area. While this approach is suitable for target sites near the earthquake epicenter, its accuracy in estimating ground shaking is relatively low (Kanamori, 2005).

The second approach is the regional EEWS, as illustrated in Figure 1. This system operates by establishing a network of seismometers as close as possible to the earthquake epicenter. When an earthquake occurs, these sensors rapidly detect and determine the earthquake's magnitude and location. Subsequently, this information is used to predict ground shaking in specific regions through Ground Motion Prediction Models (GMPM) (Mittal et al., 2022). An early warning is issued if the estimated shaking by GMPM exceeds a predefined threshold in each area (R. M. Allen & Kanamori, 2003). This system offers higher accuracy in ground-shaking estimation and can provide warnings across a broader area, including regions without sensors (Given et al., 2018). However, it is unable to issue warnings for areas close to the epicenter (Satriano et al., 2011; Y.-M. Wu & Kanamori, 2005).

GMPM plays a crucial role within the EEW System, particularly in regional EEWS contexts. A highly accurate GMPM is essential for predicting the ground motion values generated by an Earthquake. When the GMPM underpredicts, missed alerts occur, meaning the system fails to dispatch alerts to end users, resulting in no response or action on their part. Conversely, when the model overpredicts, the system issues false alerts, prompting end users to take unnecessary actions that could cause significant costs or risks (Meier, 2017; Tan et al., 2022; Ahn et al., 2023).

1.2 Problem Statement

Indonesia, one of the most earthquake-prone countries in the world, is currently developing the EEWS to enhance its disaster preparedness and mitigation strategies. West Java Province, a region with a complex tectonic setting and a significant history of seismic events has been selected as one of the pilot projects. Indonesia plans to implement two types of EEWS: on-site and regional areas (Pramono et al., 2023).

As mentioned, a regional EEWS requires a specific GMPM to generate accurate alerts. Using GMPMs developed for other regions may lead to overprediction or underprediction of ground motions (Ashadi & Kaka, 2018; Jorjiashvili et al., 2022; Hu et al., 2023). To date, no region-specific GMPM has been developed for the West Java region highlighting a critical gap that must be addressed to enhance the system's reliability in this region.

GMPM can be developed using two methods: the traditional approach and machine learning. The traditional approach, as compiled by Douglas (2024), uses linear regression models for developing GMPM. However, this approach's weakness is its inability to capture the nonlinear behavior present in ground motion databases. To address this, additional terms and regression coefficients are needed in the linear regression model (Khosravikia and Clayton, 2021). In contrast, machine learning can effectively capture this nonlinear nature, leading to more accuracy than traditional approaches. Machine learning techniques offer several benefits in GMPM development, including the ability of nonparametric methods to directly learn ground motion model functions from data, thereby eliminating the need to assume specific regression equations. Additionally, machine learning allows the incorporation of new data or explanatory variables not typically used in conventional GMPMs (Kubo et al., 2020).

This study aims to develop GMPMs for West Java using both the traditional method and three machine learning algorithms: Random Forest, Catboost, and Gradient Boosting. By comparing the performance of these methods in terms of prediction accuracy and computational efficiency, this research will identify the most suitable model for implementation in Indonesia's EEWS.

1.3 Objective and Research Questions

The primary objective of this proposed thesis is to develop Ground Motion Prediction Models (GMPMs) for the West Java region to enhance the Indonesia Earthquake Early Warning System using traditional methods and three Machine Learning techniques: Catboost (CB), Random Forest (RF), and Gradient Boosting (GB). By developing these models, the study aims to improve the accuracy and reliability of earthquake early warning systems in predicting ground motions, which is crucial for mitigating the impact of seismic hazards in Indonesia. To achieve this goal, the following research questions will be addressed:

- What are the optimal hyperparameters for machine learning models (Random Forest, Categorical Boosting, and Gradient Boosting) to achieve the highest accuracy in Ground Motion Prediction Models for the West Java region?
- Which machine learning technique (CB, RF, GB) provides the best performance for developing GMPMs in terms of prediction accuracy and computational efficiency?
- How do traditional GMPMs compare with machine learning-based models in terms of accuracy and reliability for predicting ground motions in the West Java region?
- What are the key seismic and geological features that influence the performance of machine learning-based GMPMs in the West Java region?
- What are the uncertainties and limitations associated with using machine learning techniques for GMPMs, and how can these be addressed to improve model robustness?

The answers to these questions will provide a comprehensive evaluation of the models' performance and help determine which approach yields the most accurate and reliable predictions. This, in turn, will contribute to the enhancement of the Indonesia Earthquake Early Warning System by providing more accurate alerts for the West Java region.

CHAPTER 2

LITERATURE REVIEW

2.1 Study Area

This study focused on the West Java Region which was selected as one of the pilot project areas for implementing Indonesia's EEWS (Pramono et al., 2023). The 2020 census conducted by the Central Bureau of Statistics demonstrates that the West Java province of Indonesia holds the highest population in the country, with a total of 49,565,200 individuals recorded (approximately twice the population of Texas). Despite its critical infrastructure such as steam power plants and high-speed rail lines, the West Java region experiences frequent earthquakes. The United States Geological Survey (USGS) has recorded 530 earthquakes with a magnitude greater than 5 since 1913 as shown in Figure 2.

On November 21, 2022, an earthquake of magnitude 5.6 struck the Cianjur region, causing 600 fatalities and widespread damage to tens of thousands of homes, as reported by the National Disaster Management Agency (Supendi, Winder, et al., 2023). The event resulted in an estimated economic loss of 262 million dollars. Furthermore, a more devastating disaster known as the "tsunami earthquake" occurred on July 17, 2006, in the southern region of West Java. This earthquake, with a magnitude of 7.7, generated a tsunami along the south coast of Java, resulting in over 600 deaths and displacing 75,000 individuals (Fujii and Satake, 2006; Mori et al., 2007).

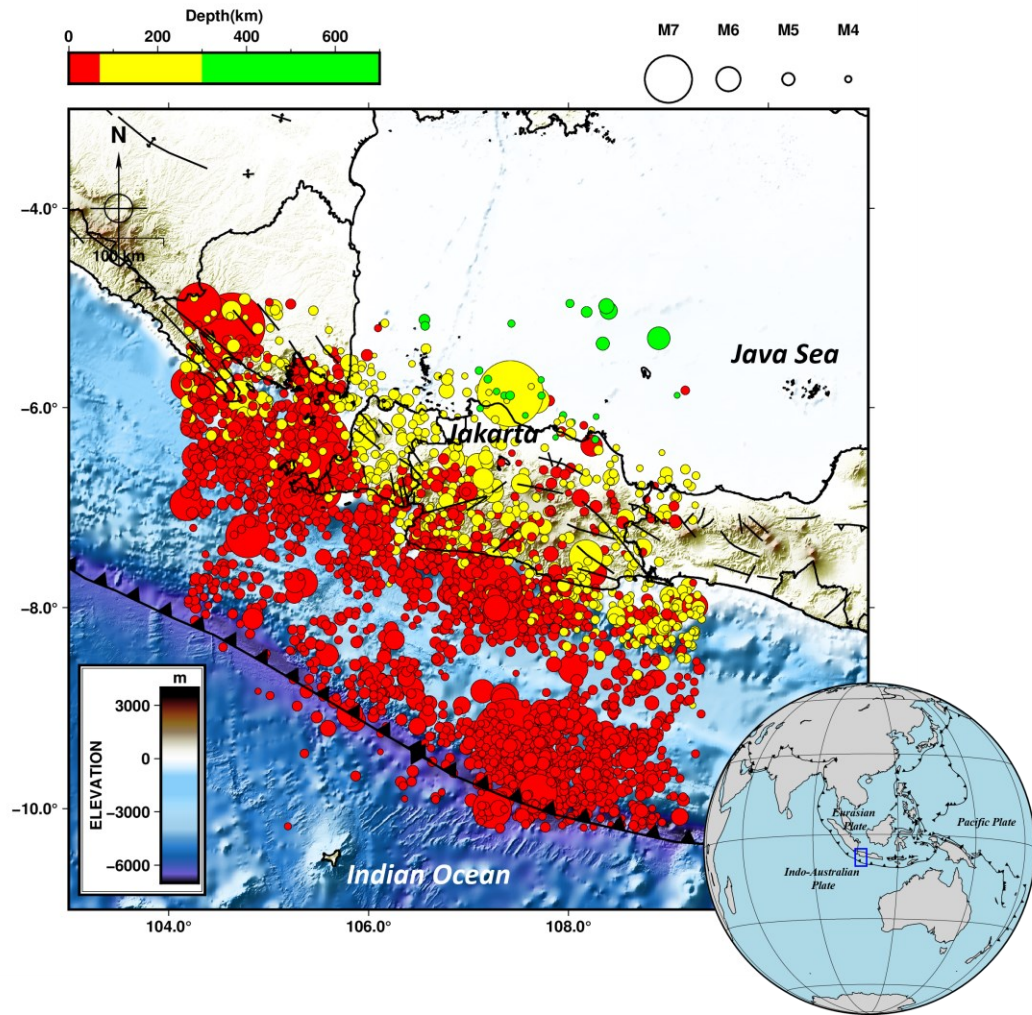


Figure 2. Map of the study area and its seismicity from 1913 to 2023 (data source: United States Geological Survey (USGS))

West Java is seismically significant due to its complex tectonic setting and the impact of the Java subduction zone and multiple fault systems. The subduction of the Indo-Australian plate beneath the Eurasian plate along Java Island has resulted in the formation of active faults, such as the Cimandiri, Lembang, and Baribis faults, within West Java (Supendi et al., 2018; Widiyantoro et al., 2022). In the southern part of this area, research has indicated the presence of a seismic gap with the potential to cause a large earthquake with a magnitude of M_w 8.9 (Widiyantoro et al., 2020; Hutchings and Mooney, 2021; Supendi et

al., 2023). These findings emphasize the necessity for ongoing research and preparation initiatives in the West Java region to reduce the consequences of earthquakes.

2.2 Previous Studies

Ground Motion Prediction Models (GMPMs) provide a means of predicting the level of ground shaking and its associated uncertainty at any given site or location, based on an earthquake magnitude, source-to-site distance, local soil conditions, fault mechanism, and other parameters. GMPM can be used for earthquake engineering as an important input in Seismic Hazard Analysis used in building code plan (Ashadi and Kaka, 2018). GMPMs are also developed for EEWS purposes as a reference for providing alerts to end-users (Satriano et al., 2011; Cremen and Galasso, 2020). Initially, the concept of developing GMPM was that a single GMPM model could be applied to various locations. However, each region has distinct geological characteristics. These differences encourage researchers to develop GMPMs that are specific to areas to achieve more accurate predictions (Chiou et al., 2010; Douglas, 2004).

GMPMs have been developed worldwide. Generally, three types of GMPMs have been developed, subduction zone earthquakes, shallow crustal earthquakes in active tectonic regions, and shallow crustal earthquakes in stable continents (Abrahamson and Shedlock, 1997). Douglas (2024) conducted an extensive compilation of published traditional GMPMs spanning from 1964 to April 2024, encompassing 505 empirical equations for predicting PGA (Peak Ground Acceleration) and 316 empirical equations for predicting spectral ordinates.

Following are some of the existing Traditional GMPMs that were developed for different regions:

1. Shallow-crustal zone

1.1. Akkar & Bommer (2010)

$$\begin{aligned} \log(PGA) = & 1.04159 + 0.9133M_w - 0.0814M_w^2 \\ & + (-2.92728 + 0.2812M_w)\log\sqrt{R^2 + 1.9664^2} \\ & + 0.08753S_S + 0.01527S_A \end{aligned} \quad (2.1)$$

Where PGA in Gal. Use three site categories: Soft soil $S_S = 1, S_A = 0$, Stiff soil $S_S = 0, S_A = 1$, Rock $S_S = S_A = 0$. They developed the GMPMs for shallow-crustal earthquakes in Europe, the Mediterranean Region, and the Middle East.

1.2. Boore et al. (2014)

$$\ln(PGA) = F_E + F_P + F_S \quad (2.2)$$

$$F_E = 1.431(M - 5.5) + 0.05053(M - 5.5)^2 \quad (2.3)$$

$$F_P = [-1.134 + 0.1917(M - M_{ref})] \ln R - 0.008088\sqrt{R^2 + 4.5^2} \quad (2.4)$$

$$F_S = -0.6 \ln\left(\frac{V_{s30}}{V_{ref}}\right) \quad (2.5)$$

Where PGA in g, $V_{ref} = 760 \text{ m/s}$, and $M_{ref} = 4.5$. They developed the GMPMs from ground motions recorded in worldwide shallow crustal earthquakes in active tectonic regimes such as Japan, New Zealand, China, Italy, Taiwan, and California. The database, known as NGA-West2, covered a parameter space with magnitudes ranging from M 3.0 to M 7.9, and distance from 0.05 to 1.533 km.

1.3. N. A. Abrahamson et al. (2014)

$$\ln(PGA) = 0.587 - 0.1(M - 6.75) - 0.015(8.5 - M)^2 + [-0.79 + 0.275(M - 6.75)] \ln \sqrt{R^2 + (5 - M)^2} - 0.1(M - 4) - 0.47 \ln\left(\frac{V_{s30}}{V_{lin}}\right) \quad (2.6)$$

Where PGA in g and $V_{lin} = 660 \text{ m/s}$. They also used the NGA-West2 database.

1.4. Campbell & Bozorgnia (2014)

$$\ln(PGA) = -4.416 + 0.984M + [(-2.773 + 0.248M) \ln \sqrt{R^2 + 6.768^2}] + 1.09 \ln(V_{s30}/V_{ref}) + (Z_{hyp} - 7)0.0977 \quad (2.7)$$

Where PGA in g, and $V_{ref} = 865 \text{ m/s}$. They used the NGA-West2 dataset.

1.5. Zhao et al. (2006)

$$\ln(PGA) = 1.101M_w - 0.00564R - \ln[R + 0.0055 \exp(1.080M)] + e(h - 15)\delta h + F_R + S_I + S_S + S_{SL} \ln(R) + C_i \quad (2.8)$$

Where PGA in Gal, $\delta h = 1$ when $h > 15 \text{ km}$. $F_R = 0.251$ for crustal event only, $S_S = 2.607$ and $S_{SL} = -0.528$ are applied for Intralab event only. $C_1 = 1.111$ for $600 \text{ m/s} < V_{s30} < 1100 \text{ m/s}$, $C_2 = 1.344$ for $300 \text{ m/s} < V_{s30} < 600 \text{ m/s}$, $C_3 = 1.355$ for $200 \text{ m/s} < V_{s30} < 300 \text{ m/s}$, and $C_4 = 1.420$ for $V_{s30} < 200 \text{ m/s}$. They developed GMPMs for both shallow crustal and subduction-zone earthquakes in Japan. The dataset includes events with magnitudes greater than M5.0 and source-to-site distances ranging from 0.5 to 300 km.

2. Subduction zone

2.1. Youngs et al. (1997)

For rock sites:

$$\ln(PGA) = -0.6687 + 1.438M_w - 2.329 \ln[R + \exp(\ln(1.907) + 0.617M_w)] + 0.3643Z_t + 0.00648D \quad (2.9)$$

For soil sites:

$$\ln(PGA) = 0.248 + 1.414Mw - 2.552\ln[R + \exp(\ln(1.778) + 0.554Mw)] + 0.3846Zt + 0.00607D \quad (2.10)$$

Where PGA is in g, $Zt = 1$ for Interface events, and $Zt = 0$ for Intralab events. D is focal depth in km. The ground motion database was obtained from earthquakes that occurred in Alaska, Mexico, Cascadia, the Solomon Islands, Peru, Chile, and Japan. The dataset includes events with magnitudes of M5.0 and greater, and source-to-site distances ranging from 10 to 500 km.

2.2. Zhao et al. (2006)

$$\ln(PGA) = 1.101Mw - 0.00564R - \ln[R + 0.0055 \exp(1.080M)] + e(h - 15)\delta h + F_R + S_I + S_S + S_{SL} \ln(R) + C_i \quad (2.11)$$

Where PGA in Gal, $\delta h = 1$ when $h > 15$ km. $F_R = 0.251$ for crustal event only, $S_S = 2.607$ and $S_{SL} = -0.528$ are applied for Intralab event only. $C_1 = 1.111$ for $600 \text{ m/s} < V_{s30} < 1100 \text{ m/s}$, $C_2 = 1.344$ for $300 \text{ m/s} < V_{s30} < 600 \text{ m/s}$, $C_3 = 1.355$ for $200 \text{ m/s} < V_{s30} < 300 \text{ m/s}$, and $C_4 = 1.420$ for $V_{s30} < 200 \text{ m/s}$.

2.3. Lin & Lee (2008)

For rock sites

$$\ln(PGA) = -2.5 + 1.205Mw - 1.905\ln[R + 0.516 \exp(0.6325Mw)] + 0.0075H + 0.275Zt \quad (2.12)$$

For soil sites

$$\ln(PGA) = -0.9 + Mw - 1.9\ln[R + 0.9918 \exp(0.5263Mw)] + 0.004H + 0.31Zt \quad (2.13)$$

Where PGA is in g, $Zt = 1$ for the ntraslab event, and $Zt = 0$ for the Interface event. Use two site categories based on NEHRP: rock for B and C type sites, and soil for D and E type sites. This GMPM was developed using data from subduction-zone earthquakes in

northeastern Taiwan, with magnitudes greater than M4.1 and source-to-site distances ranging from 20 to 600 km

2.4. N. Abrahamson et al. (2016)

$$\ln(PGA) = 4.2203 + 0.18 + [-1.35 - 0.40F_{event} + 0.1(M - 7.8)] \ln\{R + 10 \exp[0.4(M - 6)]\} - 0.0012R + 3.12F_{event} + \{0.9[M - (7.8 + 0.2)] - 0.0135(10 - M)^2\} + 0.98 \ln\left(\frac{V_{s30}}{865}\right) \quad (2.14)$$

Where PGA is in g, $F_{event} = 0$ for Interface event, and $F_{event} = 1$ for Intralab event.

The database used to develop the GMPM in this study is derived from a global dataset of subduction-zone earthquakes, with magnitudes ranging from M5.0 to M8.4 and source-to-site distances of up to 300 km

2.5. Ashadi & Kaka (2018)

For Interface event

$$\log(PGA) = -0.7957 + 0.3418M_w + 0.0026H - 0.0019R - 10^{(0.4669-0.202M_w)} \log R + 0.1789St \quad (2.15)$$

For Intralab event

$$\log(PGA) = -1.5737 + 0.5367M_w + 0.0047H - 0.0037R - 10^{(1.7869-0.4605M_w)} \log R + 0.229St \quad (2.16)$$

Where PGA is in Gal. $St = 1$ for soil sites ($V_{s30} < 350 \text{ m/s}$), and $St = 0$ for $350 \text{ m/s} < V_{s30} < 1500 \text{ m/s}$. They used strong motion data from subduction-zone earthquakes that occurred in Java and Sumatra, Indonesia. The dataset includes events with magnitudes ranging from M4.8 to M8.6 and source-to-site distances between 100 and 800 km.

The utilization of machine learning techniques in the field of ground motion prediction has witnessed significant growth in recent years. In a study by Khosravikia & Clayton (2021),

various machine-learning techniques were explored for predicting ground motion intensity. The study considered source characteristics, source-to-site distance, and local site conditions. It investigated the potential advantages of employing alternative machine learning methods such as ANN, Random Forest, and Support Vector Machine. These algorithms were trained on a dataset comprising 4528 ground motions, including 376 seismic events with magnitudes ranging from 3 to 5.8. These events were recorded over distances spanning from 4 to 500 km in Oklahoma, Kansas, and Texas since 2005. The findings indicated that when an adequate amount of data is available, alternative machine learning algorithms tend to provide more accurate predictions compared to the traditional linear regression-based method. Notably, Random Forest emerged as particularly effective. However, the conventional method remains valuable in scenarios with limited data availability.

In the study by Seo et al. (2022), GMPMs were developed to estimate seismic intensity in South Korea using machine-learning techniques, including ANN, Random Forest (RF), and Gradient Boosting (GB). The dataset encompassed 1189 ground motions recorded during 77 earthquakes ($M_L > 3.0$), including significant events like the Gyeongju and Pohang earthquakes. Comparative analysis revealed that the GB-based model outperformed the other models based on multiple evaluation metrics, including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), standard deviation of residuals, and between-event and within-event residuals. Variable importance analysis highlighted the significance of variables like earthquake magnitude (M_L) and epicentral distance (R_{epi}). The GB-based model effectively predicted Peak Spectral Accelerations (PSAs) for recent earthquakes with $M_L > 3.0$ and generated

maps of estimated PSA (PSA_{est}) values for various periods, including a scenario earthquake with an M_L of 5.0.

In the study conducted by Wang et al. (2023), the complex relationship between site conditions and seismic ground motion, a crucial aspect of earthquake hazard analysis, was investigated. Recent advancements in machine learning offered a promising avenue for predicting site amplification effects. The study leveraged data from 698 KiK-net stations, comprising 353,327 records collected between 1997 and 2019. Six critical parameters were analyzed, including Vs30, earthquake magnitude, epicentral distance, earthquake source depth, bedrock ground motion, and altitude. Three machine learning algorithms, namely Random Forest, XGBoost, and Deep Neural Networks were employed to predict site amplification factors.

The results showcased the superiority of all three machine learning algorithms over traditional GMPMs, with XGBoost demonstrating the most robust performance. What set this study apart was its ability to provide comprehensive explanations for the predictive models' outcomes, achieved through the Shapley Additive explanation (SHAP) method. This method highlights the relative importance of six parameters in predicting site amplification, offering a valuable contribution to ground motion prediction and seismic hazard analysis.

2.3. Ground Motion Parameters

Ground motion parameters, including Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), Peak Ground Displacement (PGD), and Spectral Acceleration (SA), are essential in evaluating seismic hazards and designing earthquake-resistant structures. Each

parameter provides unique insights into how the ground and structures respond during an earthquake, offering critical data for engineers and seismologists.

Peak Ground Acceleration (PGA) is one of the most used ground motion parameters and represents the maximum acceleration of the ground at a specific location during an earthquake. It directly correlates with the forces experienced by structures, making it a fundamental measure in seismic design and engineering (Kramer & Stewart, 2024). PGA is also widely used in estimating the level of earthquake damage in target areas in the EEWS (R. M. Allen, 2006; Y. Liu et al., 2024; Y. Wu et al., 2018).

Peak Ground Velocity (PGV) measures the maximum velocity at which the ground shakes during an earthquake. PGV is less sensitive to the higher-frequency components of the ground motion. Thus, the PGV is good for characterizing ground motion amplitude at intermediate frequencies. For structures or facilities that are sensitive to intermediate frequencies such as tall buildings (above 7 stories), bridges, etc., PGV can provide a more accurate indication of damage compared to PGA (Kramer & Stewart, 2024).

Peak Ground Displacement (PGD) captures the maximum displacement of the ground during an earthquake. It is associated with the lower-frequency components of an earthquake. However, it can be difficult to determine accurately Campbell (1985) due to signal processing problems in the filtering and integration of accelerograms and due to long-period noise. As a result, peak displacement is less typically utilized to quantify ground motion than peak acceleration or peak velocity (Kramer & Stewart, 2024).

Spectral Acceleration (SA) is a parameter that measures the maximum acceleration of a structure or system modeled as a simple harmonic oscillator at a particular frequency or period. SA is critical in assessing how structures respond to different frequencies of ground shaking, making it fundamental in seismic hazard assessments and meeting building code requirements. By evaluating SA at various spectral periods, engineers can design buildings that are better equipped to handle the complex vibrations induced by earthquakes (Kramer & Stewart, 2024; Newmark & Hall, 1982).

2.4. Magnitude Conversion

The earthquake catalog usually includes various types of magnitudes, such as m_b , m_B , M_L , $M_w(m_B)$, M_{wp} , $M_w(M_{wp})$, M_w , and M . A homogeneous catalog is crucial for studying earthquake occurrence patterns both spatially and temporally. It is also widely applied in engineering fields, including seismic hazard assessment, peak ground acceleration estimation, and the determination of seismic strain levels (Scordilis, 2006; Tan et al., 2022). Therefore, these different magnitude types need to be converted into a single, consistent magnitude type. Moment magnitude (M_w) is chosen because it is calculated based on the seismic moment of an earthquake, which is not affected by saturation effects at high values (Das et al., 2019; Hanks & Kanamori, 1979). BMKG has developed a formula to convert these magnitude types into moment magnitudes using earthquake data from the Indonesian region, employing linear regression as shown in Table 1.

Table 1. Empirical Equations for Magnitude Conversion.

Magnitude Type	Entries	Linear Equation	Correlation Coefficient
ML _v	224	$M_w = 0.8736ML_v + 0.3078$	0.8079
Mb	226	$M_w = 1.198mb - 1.2053$	0.7821
mB	226	$M_w = 1.1426mB - 1.3386$	0.7747
M _w (mB)	226	$M_w = 0.8737M_w(mB) + 0.6037$	0.7741
M _w p	175	$M_w = 0.918M_{wp} + 0.3472$	0.6056
M _w (M _w p)	175	$M_w = 0.7041M_w(M_{wp}) + 0.16691$	0.6051

2.5. Source-to-site Distance Measures

Source-to-site distances describe the decrease in ground motion values due to anelastic and geometric attenuation as the seismic waves propagate away from the earthquake source. According to Edwards & Fäh (2014), there are two main groups commonly used to calculate the distance between an earthquake source and a recording station: point source and finite fault. The differences between the two are illustrated in Figure 3. For point source distances, there are two types: the hypocentral distance (R_{hypo}), which is the sloped distance between the hypocenter and the observer station, and the epicentral distance (R_{epi}), which is the horizontal distance between the surface projection of the hypocenter and the observer station. Finite fault distances are also divided into two types. The first is the rupture distance (R_{rup}), the shortest distance from the fault plane to the site. The second is the Joyner-Boore distance (R_{JB}), which is the shortest distance from the fault plane's surface projection to the site. When calculating ground motion using traditional approaches, the

user must ensure that the selected distance type matches the one used in developing the GMPM.

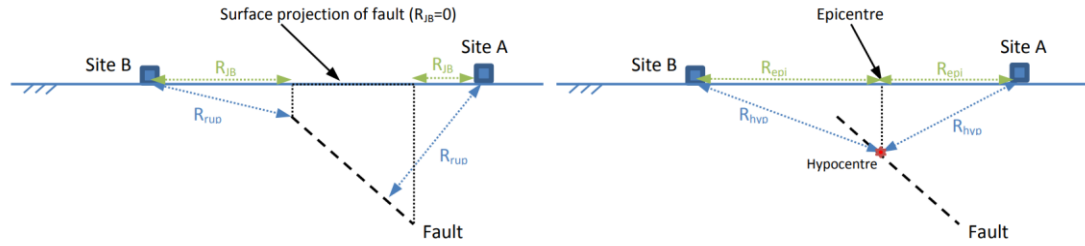


Figure 3. Distance metrics, a cross-section of a fault. (left) Finite measures of distance and (right) point-source measures of distance (Edwards & Fäh, 2014).

2.6. Local Site Conditions

The propagation of seismic waves from the earthquake source in the bedrock layer to the surface causes changes in amplitude. These changes are significantly influenced by local site conditions, which describe the type of deposits beneath the site. One of the parameters that can describe local site conditions is $Vs30$, the average shear wave velocity at depths of less than 30 meters at a given site. $Vs30$ can be obtained by various methods, such as direct measurement using Multichannel Analysis of Surface Waves (MASW), deriving $Vs30$ from topographic slopes as proposed by Allen et al. (2007), or estimating it using the site's predominant period (Muzli et al., 2021; Zhao et al., 2006). The National Earthquake Hazards Reduction Program (NEHRP) categorizes the local site conditions based on $Vs30$ values, as shown in Table 2.

Table 2. NEHRP site classifications based on V_{s30}

Category	Description	V_{s30} (m/s)
A	Hard Rock	≥ 1500
B	Rock	750 – 1500
C	Soft Rock	350 – 750
D	Stiff Soil	175 – 350
E	Soft Soil	< 175

2.7. Site altitude and slope angle

The slope angle and altitude (slope height) influence ground motion during an earthquake due to the topographic amplification effect (Tripe et al., 2013; Zhang et al., 2018). Steeper slopes are more prone to amplifying seismic waves because the waves tend to reflect and focus energy near the slope crest, leading to increased shaking compared to non-slope areas (Li et al., 2024). Ashford et al. (1997) noted that the effect of topography is most apparent for slopes steeper than 60° and tends to decrease with shallower slope angles. The slope angle represents the angular inclination of a surface relative to a horizontal plane and can be calculated as the inverse tangent of the ratio between the vertical rise and the horizontal run of the surface as in equation 2.17.

$$\theta = \tan^{-1}\left(\frac{\text{rise}}{\text{run}}\right) \quad (2.17)$$

2.8. Earthquake Classification

GMPMs are divided into three types based on tectonic settings: shallow-crustal, interface, and Intralab. This classification is because the material properties of these three categories are different, resulting in various characteristics and requiring different GMPMs. This is evidenced by Youngs et al. (1997), and Zhao et al. (2006) where the response spectra of earthquakes in the three tectonic categories are very different, with Intralab events

producing short-period spectra that are much higher than the other two categories. Erdik & Durukal (2004) also note that subduction zone events produce ground motion with a slower rate of attenuation compared to events originating from shallow-crustal.

There are several schemes for classifying earthquakes. Zhao et al. (2015) proposed an earthquake classification scheme for Japan. They stated that shallow-crustal events occur within the Earth's crust, with a hypocenter depth of less than 25 km. Interface events occur at the boundary between the oceanic and continental plates, typically at depths of less than 50 km. Intraslab events, on the other hand, are earthquakes that occur within the subducting slab. Rudyanto (2014) classifies earthquakes in Indonesia based on the following criteria: shallow-crustal events occur at distances greater than 200 km from the trench and at depths of less than 40 km. Intraslab events are defined as earthquakes with depths greater than 40 km. For earthquakes located less than 200 km from the trench and at depths of less than 40 km, careful inspection is required to determine whether the event is an interface or Intraslab earthquake, using focal mechanism analysis. If the focal mechanism is thrust, the event is classified as an interface earthquake, whereas it is normal, it is classified as an Intraslab earthquake.

2.9. Machine Learning Algorithms

2.9.1. Random Forest

A single decision tree often suffers from high variance and overfitting, meaning it can model the training data very closely but fails to generalize well to new data, and unseen data (Seo et al., 2022). To address these weaknesses, the Random Forest algorithm constructs multiple decision trees using a technique called bootstrap sampling. RF,

introduced by Breiman (2001), is one of the supervised machine learning algorithms used for both classification and regression tasks. For regression tasks, given a dataset with n samples, N bootstrap samples are created by randomly sampling n data points with replacement, which ensures that some data points may be repeated while others may be omitted. Each bootstrap sample is used to build an individual decision tree. At each node in a tree, a random subset of f features is selected from the total F features to determine the best split based on variance reduction. This introduction of randomness helps to reduce overfitting and increase model robustness. Each tree is grown to its maximum possible depth without any simplification. For predicting the output of new data points, the Random Forest algorithm aggregates the predictions by averaging the outputs from all the individual trees, which can be described as follows:

$$\ln(PGA^{pred}) = \frac{1}{N} \sum_{n=1}^N T_n(x) \quad (2.26)$$

Where N is the number of trees, $T_n(x)$ is the prediction from each tree. Figure 4 shows the architecture of the RF algorithm implementation for ground motion prediction. As seen in the figure, Mw (moment magnitude), $Repi$ (epicentral distance), depth, $Vs30$ (average shear-wave velocity to 30 meters depth), slope angle, and site altitude are set as independent variables, while the output is the average of all predictions made by each tree.

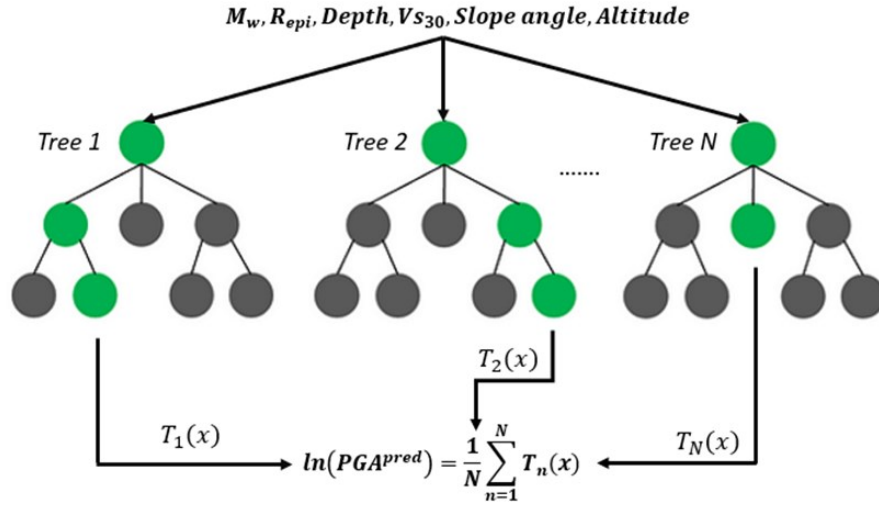


Figure 4. The architecture of the Random Forest (RF) algorithm.

2.9.2. Gradient Boosting

Though both GB and random forest belong to ensemble learning, they differ significantly. In random forests, all decision trees are built simultaneously, and the result is the weighted average. Conversely, GB builds one decision tree at a time, using the residuals from previous trees rather than making a direct prediction. Each new decision tree is based on correcting the residuals left by the previous ones (Friedman, 2001).

Figure 5 depicts the architecture of GB to predict ground motion values. Here is a detailed explanation of how GB generates a model prediction using residual decision trees. Initially, a naive prediction is made, which is the average value of $PGA^{mea}(F_0(x))$ from the training dataset, serving as the baseline model. To improve prediction accuracy, GB calculates the residual (r_{in}) for each tree index n and data sample i . The residual is the difference between the mean of the observed value and the predicted value from the current model. Minimizing this residual leads to better prediction results. The formula to calculate the residual is:

$$r_{in} = \ln(PGA_i^{mean}) - F_{n-1}(x_i) \quad (2.27)$$

where $F_{n-1}(x_i)$ is the predicted PGA by the previous model, which includes the sum of F_0 and the outputs from all trees up to $n - 1$ index.

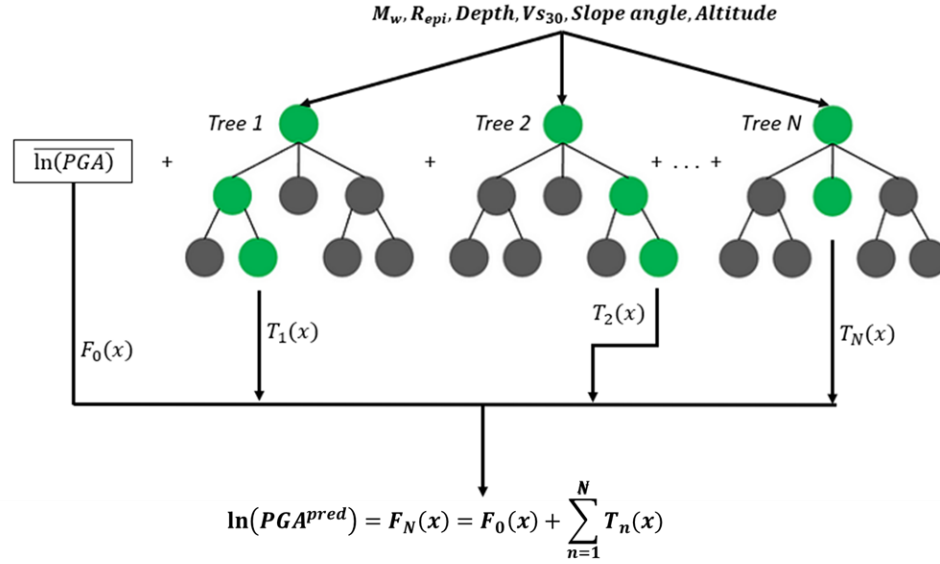


Figure 5. The structure of the Gradient Boosting (GB) algorithm.

Once the residuals are obtained, GB matches $T_n(x)$ with the dataset by training the tree using the dataset (x_i, r_{in}) . Tree $T_n(x)$ predicts the output as the mean residual. This prediction is then added to the initial prediction $F_0(x)$ to reduce the residual. GB employs a learning rate (v) when adding $T_n(x)$ to $F_0(x)$ to prevent overfitting on the training data. The learning rate ranges between 0 and 1.

$$F_N(x) = F_0(x) + v \cdot T_n(x) \quad (2.28)$$

The next step involves creating a new regression tree using the same features from the training dataset, but now the target is the updated residual obtained from the previous tree.

We then iterate this process until the model predictions stop improving. This yields the final prediction model that will be used to predict $\ln(\text{PGA}^{\text{pred}})$.

2.9.3. Categorical Boosting (Catboost)

CatBoost is an ensemble learning algorithm developed to enhance the gradient boosting method. Created by Yandex in 2017, it follows the same principle as traditional gradient boosting, combining the strengths of multiple weak learners to produce a more accurate predictive model (Dorogush et al., 2018). However, CatBoost stands out due to two critical innovations: ordered boosting and its ability to handle categorical features efficiently.

Traditional gradient boosting methods often suffer from prediction shifts caused by target leakage, particularly when the entire dataset is used to determine splits. CatBoost resolves this issue with ordered boosting—a technique that generates multiple permutations of the data and uses only past observations for each permutation when calculating leaf values. This approach significantly minimizes the risk of overfitting (Prokhorenkova et al., 2019).

Most machine learning methods cannot process categorical data directly. Typically, categorical features need to be converted into numerical representations using techniques like one-hot encoding or label encoding. In contrast, CatBoost can handle categorical data directly, automatically determining the most effective way to represent categorical features. This capability greatly reduces preprocessing efforts while preserving essential information (Dorogush et al., 2018; Prokhorenkova et al., 2019).

In addition to these key features, CatBoost is also recognized for its use of Symmetric Trees. At each depth of the tree, CatBoost applies splits based on the same feature for all nodes. This structured and predictable approach differs from other boosting algorithms that

rely on asymmetric tree structures. Symmetric trees offer several advantages such as faster training, lower memory consumption, and effectiveness with large dataset (Sharchilev et al., 2018).

2.10. Hyperparameter Tuning

Hyperparameters are variables that determine how a model is trained. They organize the learning process rather than being learned from a dataset and are usually set before the training process begins. Hyperparameter selection significantly impacts model accuracy, generalization, and other metrics (Feurer Matthias and Hutter, 2019). Therefore, to achieve an accurate model, we need a way to choose the best hyperparameters. This process is called hyperparameter tuning. In hyperparameter tuning, the goal is to find the best combination of hyperparameter values and prevent overfitting.

Each machine learning algorithm has its essential hyperparameters. In Random Forest, *n_estimators*, *max_depth*, and *min_samples_split* are several key hyperparameters that must be set before the training process. In Gradient Boosting, *learning_rate* is important as it regulates each weak learner's contribution by adjusting the shrinkage factor. While in CatBoost, *l2_leaf_reg* is used to prevent overfitting by adding a penalty term to the loss function.

There are several methods in hyperparameter tuning. The first is manual search, which usually requires an empirical approach to find the best combination of hyperparameters. This method is often used when the number of hyperparameters is relatively small, and the model is simple. This method requires a lot of effort but does not guarantee the best results (Dang et al., 2024).

Grid Search is a method for tuning hyperparameters by systematically testing all possible combinations within a defined range. For each hyperparameter, a range of values is specified, and a grid of all possible combinations is created. The model is then trained and evaluated for each combination to find the optimal settings. Grid Search is straightforward to implement and ensures a thorough exploration of the search space. However, it can be computationally intensive, especially for large search spaces, as the number of combinations grows exponentially. It is most effective for smaller search spaces or when computational resources are sufficient (Matthias & Hutter, 2019).

The third method is randomized search which is a method used to find the optimal value of a hyperparameter in a machine learning model more efficiently than Grid Search. This method works by randomly testing hyperparameter combinations from a defined space, rather than trying all possible combinations. The process involves defining a hyperparameter space, randomly selecting combinations, training a model and evaluating its performance for each combination, and selecting the combination with the best performance (Quan, 2024). The main advantages of Randomized Search are its efficiency in time, especially when dealing with large hyperparameter spaces, and its ability to explore various combinations. However, this method does not guarantee finding the best combination systematically because it only performs random sampling, so not all combinations are tested (Matthias & Hutter, 2019).

The last method is Bayesian Hyperparameter Tuning which is a method for optimizing hyperparameters in machine learning models with an efficient probabilistic approach. This method starts by creating a probabilistic model of the objective function, which describes the model's performance based on the given hyperparameters, often using Gaussian

Processes (GP) as the probabilistic model. Instead of evaluating the objective function directly, Bayesian Tuning uses a surrogate model to estimate the outcome of hyperparameter combinations, updated iteratively based on the results of previous evaluations (Dang et al., 2024). An acquisition function selects the next hyperparameter combination, evaluating the trade-off between exploring new and exploiting combinations that have shown good results. This process is repeated iteratively, with each iteration involving hyperparameter evaluation, surrogate model updates, and selection of the most promising hyperparameters (Frazier, 2018).

CHAPTER 3

METHODOLOGY

3.1. Data Collection

This study utilizes two main data groups: source and path characteristic data, and local site condition data. The source and path data were obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG) and include strong ground motion recordings such as Peak Ground Acceleration (PGA), earthquake parameters (e.g., magnitude, epicenter location, focal depth, and origin time), and accelerograph sensor locations. We used recorded PGA data from 2010 to 2023, with data from 2024 reserved for validation purposes. In total, 3561 PGA recordings from 364 earthquakes were recorded by accelerograph sensors across West Java.

The local site condition data includes $Vs30$ values and topographic information from 60 sensors. The local site conditions were classified using $Vs30$. $Vs30$ data were obtained from several published research. Some $Vs30$ values were measured using the Multichannel Analysis of Surface Waves (MASW) method, as reported by Rudyanto (2014) and Prakoso & Sukanta (2015). They were also derived from the dominant period of the site, based on research by Muzli et al. (2021). The remaining $Vs30$ values were estimated using topographic slope as a proxy, with data sourced from the United States Geological Survey (USGS). The topography data was obtained from Digital Elevation Models (DEMs) acquired from the BIG (Geospatial Information Agency of Indonesia). The distribution of the earthquakes and sensors used in this study is illustrated in Figure 6.

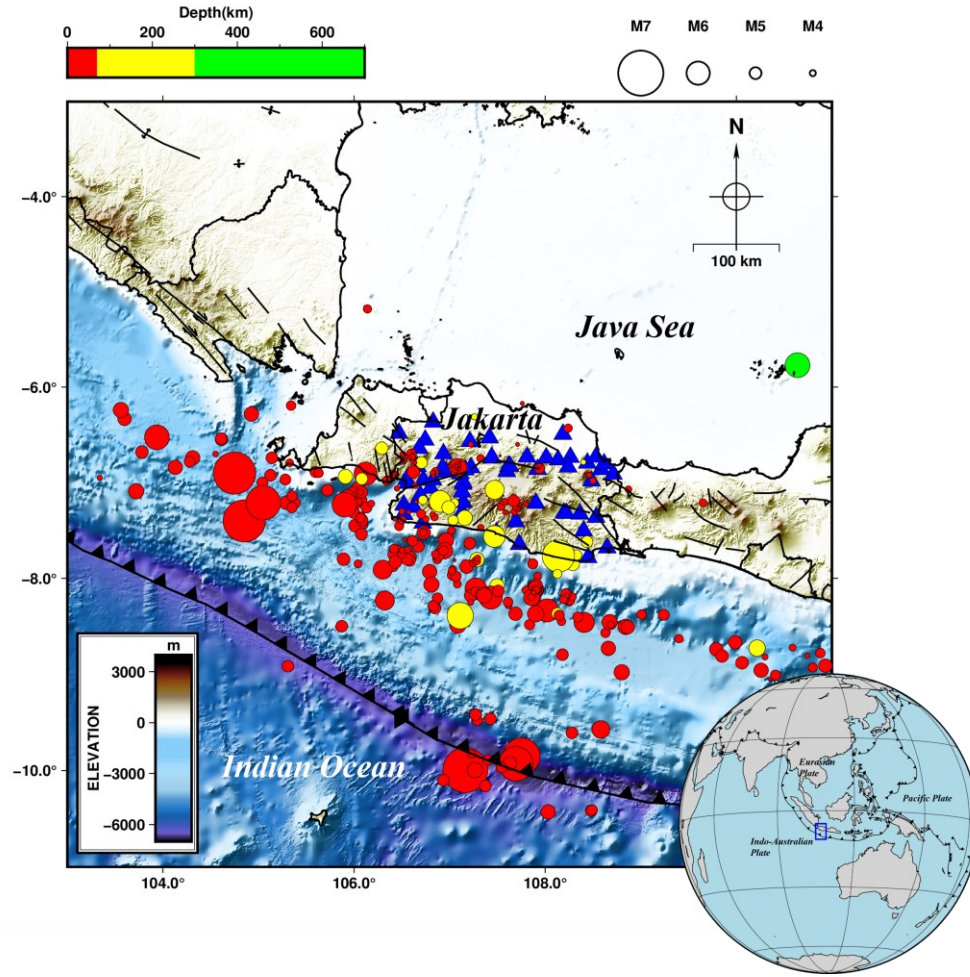


Figure 6. Earthquakes and accelerograph (blue triangle) distribution used in this study

3.2. Data Preparation

The collected data is prepared before being used in the training process. In the preparation process, several stages are carried out as follows:

1. **Conversion of Magnitude Types:** Various types of magnitudes obtained from BMKG are converted into moment magnitudes using empirical equations developed by BMKG as shown in Table 1.

- 2. Calculation of Epicentral Distance:** The epicentral distance is calculated using equation 3.1, which utilizes the coordinates of the earthquake epicenter and the observer station.

$$R_{epi} = \sqrt{(X_h - X_s)^2 + (Y_h - Y_s)^2 + (Z_h - Z_s)^2} \quad (3.1)$$

Where:

$$X_s = R * \cos\phi_s * \cos\theta_s$$

$$Y_s = R * \cos\phi_s * \sin\theta_s$$

$$Z_s = R * \sin\phi_s$$

$$X_h = (R - h) * \cos\phi_h * \cos\theta_h$$

$$Y_h = (R - h) * \cos\phi_h * \sin\theta_h$$

$$Z_h = (R - h) * \sin\phi_h$$

$$\phi_s = \text{Latitude of the station}$$

$$\phi_h = \text{Latitude of the epicenter}$$

$$\theta_s = \text{Longitude of the station}$$

$$\theta_h = \text{Longitude of the epicenter}$$

$$R = \text{Earth radius (6371 km)}$$

- 3. Classify Local Sites:** 60 accelerograph sites are classified based on the NEHRP classification.
- 4. Classify Earthquake Types:** Earthquakes are classified into three types: Shallow-crustal, Interface, and Intralab. This classification follows the scheme proposed by Rudyanto (2014), resulting in three ground motion databases categorized by tectonic type.
- 5. Selection of Variables:** This study utilizes six explanatory variables: moment magnitude (M_w), epicentral distance (R_{epi}), focal depth, V_{s30} , slope angle, and site

altitude. The dependent variable is the natural logarithm of PGA (Peak Ground Acceleration).

6. **Dataset Visualization:** Exploring and visualizing the dataset to get an idea of the distribution and relationships between variables
7. **Data Splitting:** Each database is randomly split into 80% for training and 20% for testing.

3.3. Model Training

After completing the preparation process, the next step is to choose a model to be trained with the training dataset. This stage highlights the differences between the traditional approach and machine learning.

3.3.1. Traditional Approach

For the traditional approach, the following stages are performed:

1. **GMPM Functional Form Selection:** Select a functional form that aligns with the parameters available in the ground motion database. Some examples of functional forms are found in equations 2.1–2.16.
2. **Coefficient Modification:** The coefficients of the selected functional form are modified using the least squares method to improve the model's fit.

3.3.2. Machine Learning Approach

For the machine learning approach, the following steps are undertaken:

1. **Hyperparameter Tuning:** Three hyperparameter tuning methods—Grid Search, Randomized Search, and Bayesian Optimization—are applied to optimize the models. In this stage, considering our small-moderate dataset size, 5-fold cross-

validation is applied. This approach retains more training data and obtains a more reliable estimate of the model's generalization performance on the test set than a single validation set alone. The performance of each hyperparameter set was assessed using the mean squared error (MSE) metric, as defined in Equation 3.3

2. **Model Training:** Three models—Categorical Boosting (CB), Random Forest (RF), and Gradient Boosting (GB)—are trained using the training dataset and the best hyperparameters obtained from the tuning process.

3.4. Model Evaluation

At this stage, the traditional approach model with its coefficients, along with the three machine learning models, and the model by Zhao et al. (2006) are evaluated using the testing dataset. The five models are compared both quantitatively and qualitatively. The qualitative comparison is performed using residual analysis, while the quantitative comparison utilizes three evaluation metrics as follows:

1. Pearson Correlation Coefficient (R)

It shows the correlation between observed and predicted values. The higher the R-value, the higher the accuracy of the predicted value produced by the model. It can be calculated as follows:

$$R = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (3.2)$$

2. The Coefficient of Determination (R²)

A statistical metric used to measure how well a regression model explains the variability in the data. The R² value ranges from 0 to 1, where 0 means the model

cannot explain the variability, and 1 means the model explains all the variability in the data. R^2 can be calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (x_i - y_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (3.3)$$

3. Mean Square Error (MSE)

This evaluation metric calculates the mean squared error between observed and predicted values. The smaller the value, the more accurate our model is in predicting. It is defined as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 \quad (3.4)$$

4. Standard deviation of residual

It measures the average distance between predicted data and the regression line.

The formula is:

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \mu)^2} \quad (3.5)$$

Where n is the number of data points, x_i represents observed values and y_i represents predicted values, $\bar{x}$ is the mean of the observed $\ln(\text{PGA})$, $\bar{y}$ mean of the predicted $\ln(\text{PGA})$, and μ is the mean of the residuals.

3.5. Model Explanation and Validation

After evaluating and comparing all models, the best-performing model is analyzed using the Shapley Additive Explanation (SHAP) method to identify which variables most influence the prediction of the dependent variable. Next, the best models are further validated using observed data from an earthquake that occurred in 2024, which was not

included in the original database. This step ensures the model's robustness and generalizability.

The flowchart of this study is presented in Figure 7.

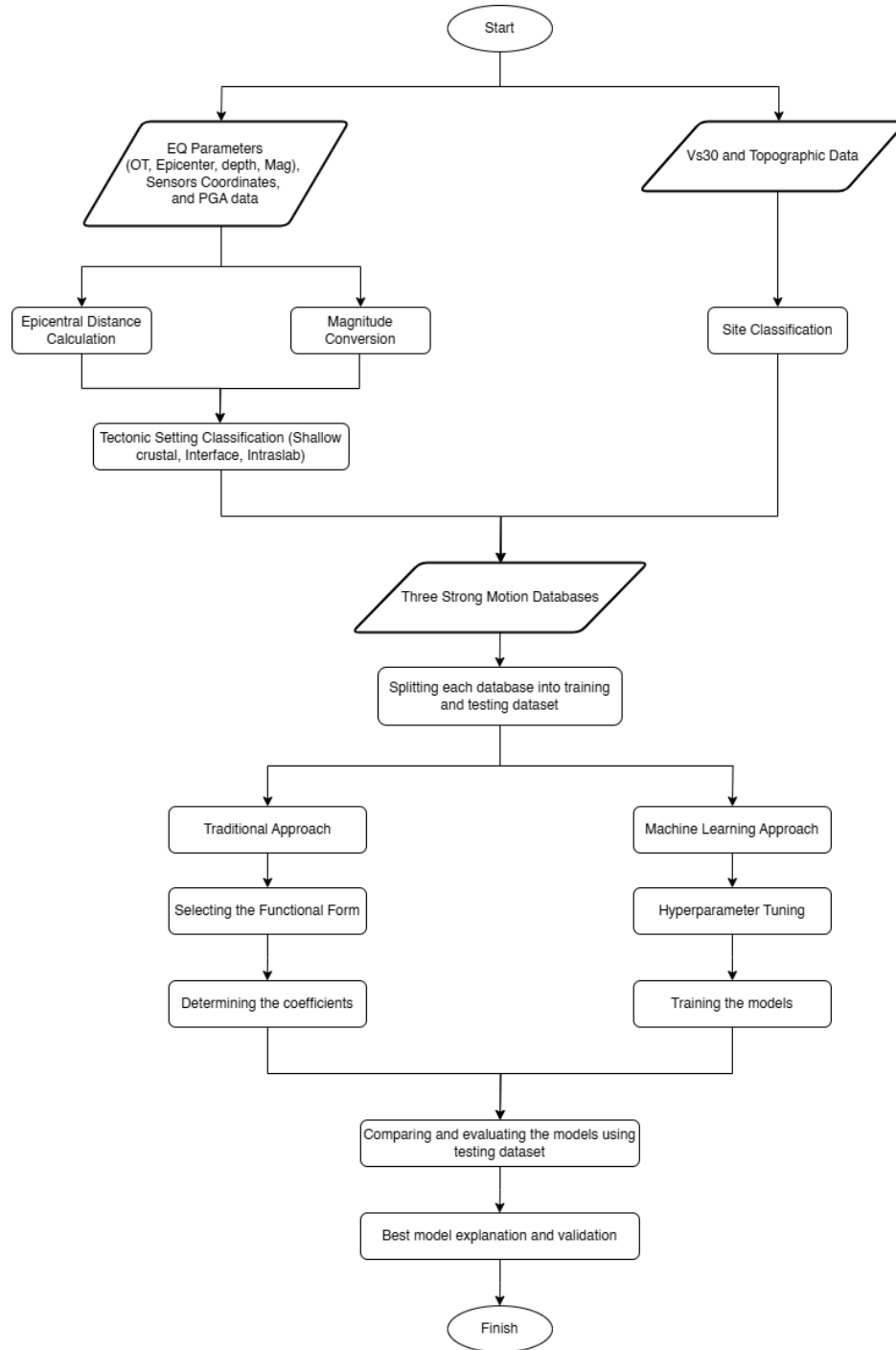


Figure 7. Flowchart of this study

CHAPTER 4

RESULT AND DISCUSSION

4.1. Data Preparation

4.1.1. Local Site Conditions

We utilize V_{s30} data, slope angle, and site altitude to depict local site conditions. V_{s30} data for eight sites are obtained through direct measurements using the Multichannel Analysis of Surface Waves (MASW) method (Rudyanto 2014; Prakoso and Sukanta, 2015), 25 sites are determined using the predominant period method (Muzli et al., 2021), while the rest is derived from topographic slope information provided by the USGS (United States Geological Survey). Slope angle and site altitude are derived from Digital Elevation Models (DEMs) acquired from the BIG (Geospatial Information Agency of Indonesia).

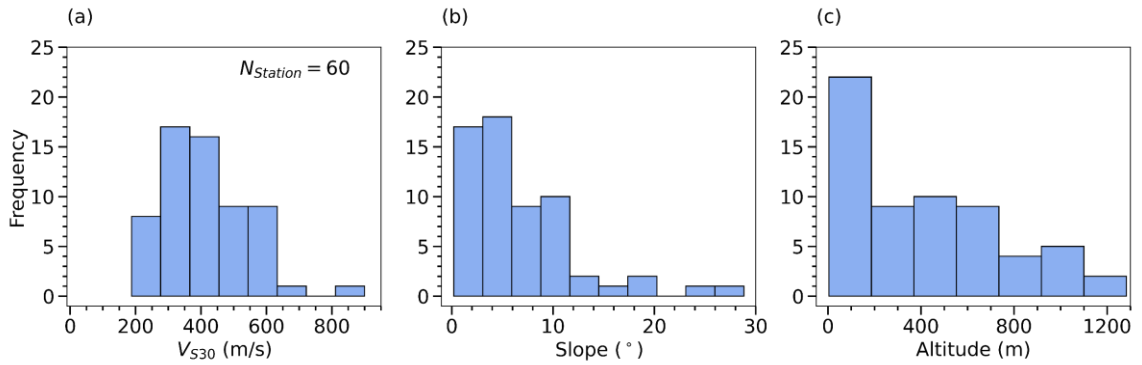


Figure 8. The histogram of the 60 local site effects. (a) V_{s30} (b) Slope angles, (c) Site altitude.

Figure 8 illustrates the distribution of the 60 local site effects used in this study. Based on NEHRP site classification, there is no station in class A (hard rock), 1 station is classified as site class B (firm to hard rock), 34 stations are categorized as class C (very dense soil and soft rock), and 25 stations as class D (stiff soil), as shown in Figure 8a. Figure 8b shows

that the observation stations are located in areas with a slope of 0-30°, with most stations situated on gentle slopes of 12°, and some on mildly sloping sites. Regarding altitude, the observation stations are located within an altitude range of 0 - 1260 MASL, as depicted in Figure 8c. For detailed information on local site conditions, refer to Table 7 in the appendix section.

4.1.2. Earthquake Classification

Earthquake classification based on tectonic type follows the scheme by Rudyanto (2014), as explained in Section 2.8. The classification is performed manually by examining the depth and distance of the epicenter from the subduction zone (trench) based on cross-section results. Figure 9 shows the distribution of epicenters and five cross-section lines. The results of the cross-sections along paths A-A' to E-E' are shown in Figure 10.

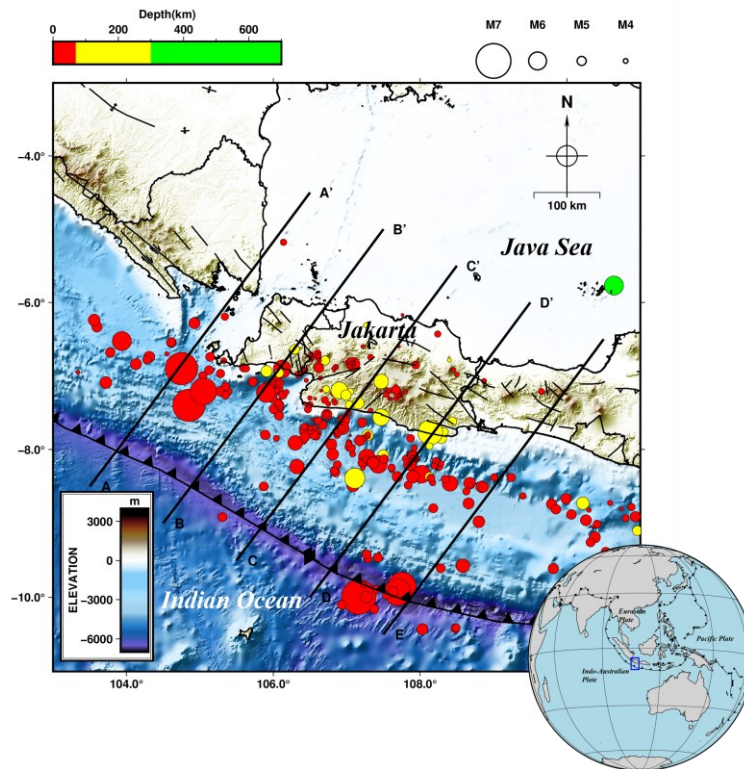


Figure 9. Epicenter distribution and five cross-section lines.

From the analysis of Figures 9 and 10, earthquake classification is determined based on tectonic types (i.e., shallow-crustal, Interface, and Intraslab). Shallow crustal earthquakes, symbolized by inverted red triangles, are located more than 200 km from the trench with depths less than 40 km. Interface earthquakes, represented by yellow circles, occur in the subduction zone at 50 km or less depths. Intraslab earthquakes, symbolized by blue diamonds, occur within the oceanic plate slab at depths greater than 50 km. The red line represents a slab model obtained from Hayes et al. (2018).

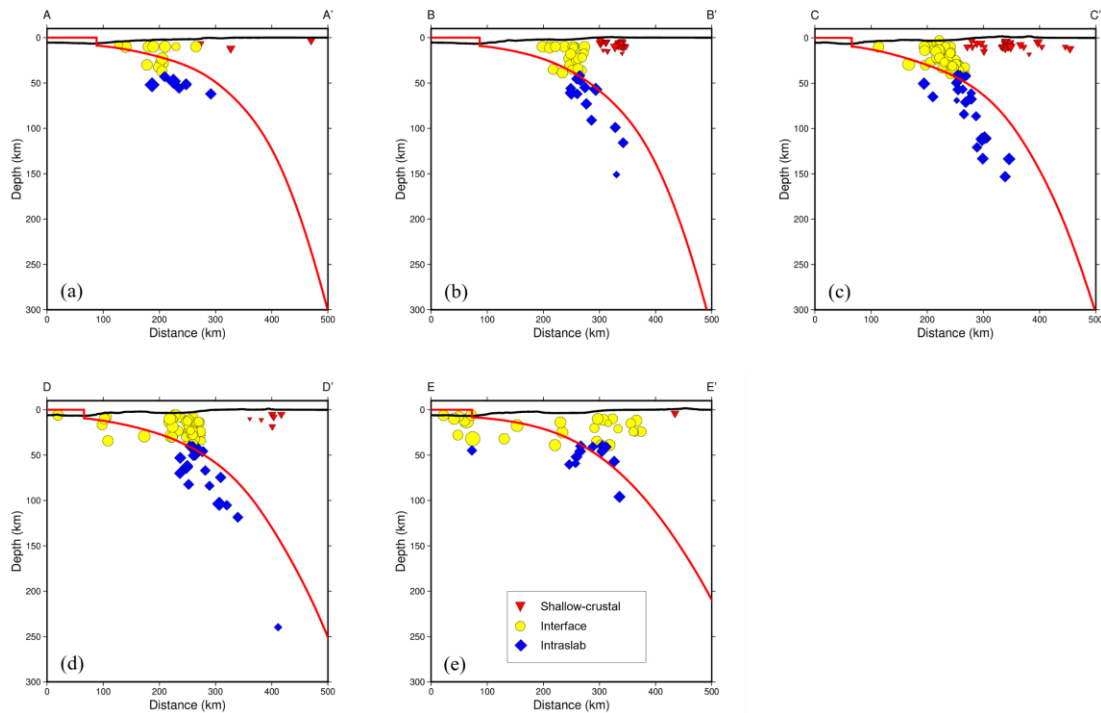


Figure 10. Cross-section view and distribution of earthquake along the lines a) A-A', b) B-B', c) C-C', d) D-D', dan e) E-E'

Figure 11 illustrates the distribution of earthquakes by tectonic type. Based on the classification results, out of a total of 383 events, 92 are identified as shallow-crustal events, 188 as interface events, and 103 as Intraslab events. Overall, the earthquakes

analyzed in this study originated from the subduction zone between the Indo-Australian and Eurasian plates.

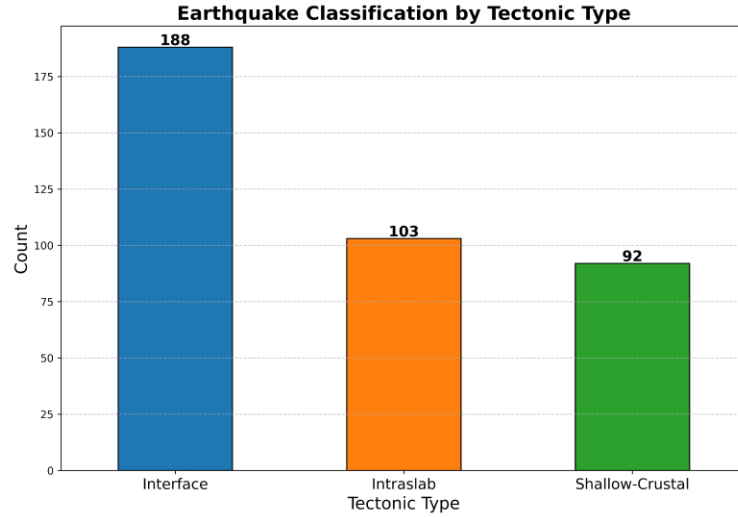


Figure 11. Graph showing the number of earthquakes categorized by tectonic type

4.1.3. Strong-motion Databases

After the earthquake classification is completed, three strong-motion databases are obtained based on tectonic type. The independent variables used include moment magnitude (M_w), epicentral distance ($Repi$), focal depth (D), $Vs30$, slope angle, and site altitude. The natural logarithm of PGA is used as the dependent variable. The predictive models for PGA can be expressed as follows:

$$\ln(\hat{Y}) = f(M_w, Repi, D, Vs30, Slope, Altitude) \quad (4.1)$$

where $\hat{Y}$ is the predicted PGA in the unit of gals (cm/s^2) and $f(\cdot)$ represents the traditional approach or machine learning techniques as either CB, RF, or GB.

1. Shallow-crustal

Shallow-crustal earthquakes in the West Java region originate from active faults such as the Lembang, Cimandiri, Baribis, Cipamingkis, and Garut Faults. These shallow-crustal earthquakes tend to cause greater damage than subduction earthquakes of the same magnitude because the faults are located under densely populated zones. This differs from subduction earthquakes, which usually occur more than 200 km from land. A total of 92 shallow-crustal earthquakes recorded by sensors in West Java produced 936 peak ground acceleration (PGA) recordings.

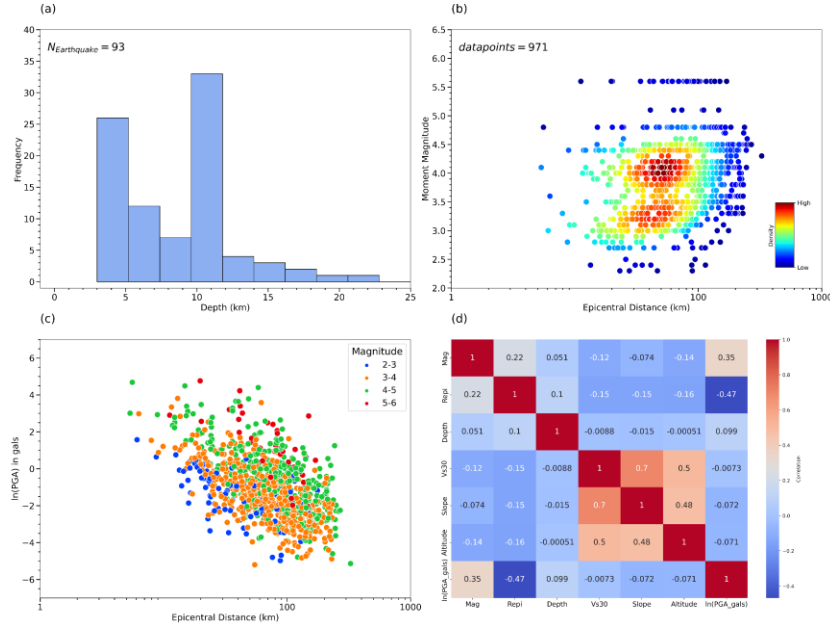


Figure 12. Distribution of feature variables for shallow-crustal earthquakes: (a) Histogram of focal depth, (b) Moment magnitude vs. epicentral distance with density overlay, (c) Scatter plot of $\ln(\text{PGA})$ vs. epicentral distance categorized by magnitude, and (d) Correlation heatmap between the variables.

Figure 12 presents a visualization of the data for shallow-crustal earthquakes. Figure 12a illustrates that these earthquakes are shallow, occurring at depths of up to 25 km. The Repi ranges from 5 to 326 km, with the majority falling between 30 and 100 km, while the moment magnitude (M_w) ranges from 2.3 to 5.6, with concentrations between 4.0 and 4.5.

Figure 12c shows the relationship between $Repi$, Mw , and $\ln(PGA)$. This plot reveals a negative correlation between $Repi$ and $\ln(PGA)$, indicating that PGA decreases as epicentral distance increases. Conversely, $\ln(PGA)$ increases with the earthquake's magnitude. Figure 12d shows the correlation between pairs of variables. It reveals that Mw has a moderate positive correlation with $\ln(PGA)$, while $Repi$ exhibits a moderate negative correlation with $\ln(PGA)$. The remaining four feature parameters show a low correlation with $\ln(PGA)$.

2. Interface

The interface earthquake in the research area resulted from the collision between the Indo-Australian plate subducting beneath the Eurasian plate. This type of earthquake has the potential to generate major to great earthquakes and can trigger tsunamis like those that occurred in Aceh (Borrero, 2005), Pangandaran (Fujii and Satake, 2006), and Mentawai (Lay et al., 2011). In this database, there are 188 interface earthquake events with 1688 PGA records.

Figure 13 illustrates the distribution of variables and their relationships for interface earthquakes. A histogram of earthquake depth shows that interface earthquakes typically occur at depths less than 40 km as illustrated in Figure 13a. Figure 13b indicates that epicentral distances ($Repi$) for these events range from 43 to 715 km, with a concentration between 88 and 170 km. Moment magnitudes (Mw) fall between 3.2 and 7, clustering around 4.5 to 5. Figure 13c demonstrates the relationship between $\ln(PGA)$, epicentral distance ($Repi$), and moment magnitude (Mw). As observed in shallow-crustal earthquakes, $\ln(PGA)$ decreases with increasing $Repi$ and increases with increasing Mw . Figure 13d shows the correlation between pairs of variables. It shows that $Repi$ has the highest

correlation with $\ln(\text{PGA})$, followed by slope angle and M_w . The remaining three feature parameters show a very low correlation with $\ln(\text{PGA})$.

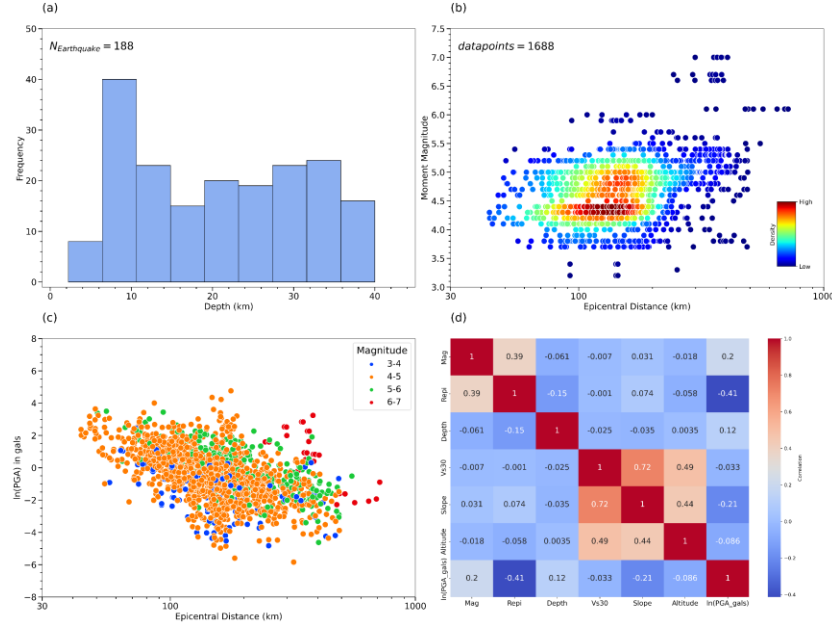


Figure 13. Distribution of feature variables for interface earthquakes: (a) Histogram of focal depth, (b) Moment magnitude vs. epicentral distance with density overlay, (c) Scatter plot of $\ln(\text{PGA})$ vs. epicentral distance categorized by magnitude, and (d) Correlation heatmap between the variables.

3. Intralab

Intralab earthquakes in the research area originated from the Indo-Australian plate, located to the south of the study region. In this study, I used 103 Intralab earthquake events with 937 PGA records. Figure 14 shows the distribution of Intralab earthquake variables. Figure 14a illustrates the depth distribution of this earthquake type, with depths ranging from 40 to 153 km. In Figure 14b, Repl ranges from 50 to 867 km, with a concentration between 89 and 167 km. Meanwhile, M_w ranges from 3.1 to 6.9, with a concentration between 4.5 and 5.5. Similar to shallow-crustal and interface earthquakes, the Intralab type shows a consistent relationship between $\ln(\text{PGA})$ and Repl, as well as M_w . $\ln(\text{PGA})$ decreases with increasing Repl, while it increases with higher M_w . Figure 14d presents the

correlation between pairs of variables. It shows that M_w has the highest correlation with $\ln(\text{PGA})$, followed by Repi and slope angle. The remaining three feature parameters show a very low correlation with $\ln(\text{PGA})$.

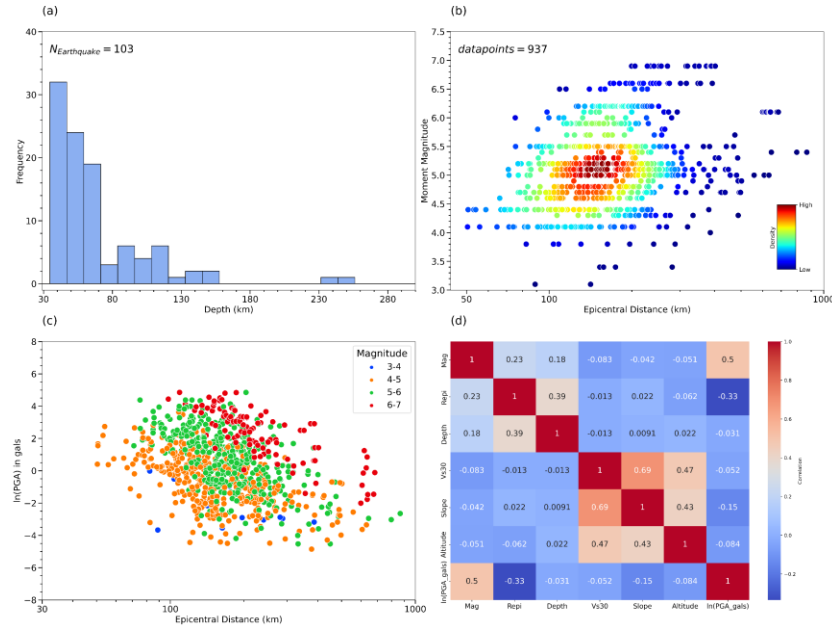


Figure 14. Distribution of feature variables for Intralab earthquakes: (a) Histogram of focal depth, (b) Moment magnitude vs. epicentral distance with density overlay, (c) Scatter plot of $\ln(\text{PGA})$ vs. epicentral distance categorized by magnitude, and (d) Correlation heatmap between the variables.

Each database was then randomly split into training and testing datasets, comprising 80% and 20%, respectively. For the Shallow-crustal database, out of 936 data points, 749 were used for training and 187 for testing. As for the 1688 PGA data points from Interface events, 1350 were allocated for training and 338 for testing. For the Intralab events, 750 were used for training, and 187 for testing.

4.2. Traditional GMPMs

We adopted the functional form proposed by Zhao et al. (2006) to develop the GMPMs for West Java's crustal, interface, and intralab regions. This decision was based on the

similarity between Japan's and Java's tectonics, both located on the overriding plates in subduction-zone systems where significant ground motion arises from the megathrust on the plate interface and earthquakes on inland faults (Muzli et al., 2018). Additionally, our compiled database was incomplete when using newer GMPM equations that require highly complex estimator parameters. Kaklamanos et al. (2011); Kale et al. (2015) concluded that a complex functional form does not always yield better results than a simpler equation. The model is defined as follows:

$$\log_e[y_{i,j}(T)] = aM_w + bx_{i,j} - \log_e(r_{i,j}) + e(h - h_c)\delta_h + F_R + S_I + S_S \quad (4.2)$$

$$+ S_{SL}\log_e(x) + C_k + \sigma$$

$$r_{i,j} = x_{i,j} + c \exp(dM_{wi}) \quad (4.3)$$

where y is the PGA (cm/s^2); M_w is the moment magnitude of the earthquake; x is the hypocentral distance in kilometers; h is the focal depth in kilometers; h_c is the depth constant for crustal events, where $h_c = 15$ km. δ_h is a dummy variable that takes a value of 1 when h is greater than h_c and 0 for other events. F_R is the coefficient parameter for reverse fault; S_I is the coefficient parameter for earthquake interface; S_S is the coefficient parameter for subduction intraslab earthquakes; S_{SL} is the modification coefficient for magnitude-distance attenuation relationship; C_k is the coefficient for site classification, and σ is the standard deviation. The subscript i is the event number and j is the number of recorded PGA of event i . The coefficients $a, b, c, d, e, F_R, S_I, S_S$, and S_{SL} are determined by regression analysis.

The training dataset from each database is used to determine the coefficients through regression analysis. Table 3 shows the coefficient values for each term from the three tectonic settings.

Table 3. Modified Coefficients by this study

Coefficients	Shallow Crustal	Interface	Intraslab
a	1.2479	1.3017	1.9367
b	-0.007	-0.0053	0.0022
c	0.0055	0.0055	0.0055
d	1.080	1.080	1.080
e	0.0602	0.0133	0.0019
f	0.0002	0.0002	0.0001
g	0.0089	0.0264	0.0002
F_R	-2.252	-	-
S_I	-	-1.693	-
S_S	-	-	5.21
S_{SL}	-	-	-2.207
S_1	1.111	1.111	1.111
S_2	1.344	1.344	1.344
S_3	1.355	1.355	1.355
S_4	1.420	1.420	1.420
σ_{res}	1.179	1.243	1.404

4.3. Machine Learning-based models

In this study, in addition to using the traditional approach, GMPMs for the West Java region were also developed using three ensemble machine learning methods: CatBoost, Gradient Boosting, and Random Forest. These three algorithms were trained and tested using the same database for each tectonic setting.

4.3.1. Hyperparameter Tuning

Hyperparameter tuning is performed to find the best combination of hyperparameters to produce an accurate prediction model. This study compares three hyperparameter tuning

techniques—grid search, randomized search, and Bayesian optimization—in terms of computation time and the average MSE obtained through 5-fold cross-validation. All three methods were evaluated using the CatBoost algorithm.

Table 4. Computation time and MSE for Catboost using various hyperparameter optimization methods

Tectonic Type	Hyperparameter Tuning Technique	Computing time (s)	MSE
Shallow-crustal	Grid Search	5846.45	0.8628
	Randomized Search	930.33	0.8972
	Bayesian Optimization	948.51	0.7431
Interface	Grid Search	6360.06	0.7114
	Randomized Search	1012.06	0.7313
	Bayesian Optimization	1028.45	0.6945
Intraslab	Grid Search	3231.33	0.7379
	Randomized Search	277.87	0.7409
	Bayesian Optimization	499.40	0.7362

Table 4 shows the computation time and MSE values for the three hyperparameter tuning methods across three tectonic settings. As seen in Table 4, the Bayesian method performs the best among the three methods in terms of MSE values across the tectonic types. In terms of computation time, Randomized Search is the fastest, slightly quicker than Bayesian, but it results in the highest MSE. Meanwhile, Grid Search takes the longest time to find the best hyperparameter combination, but its MSE values are not better than those of Bayesian. Therefore, in this study, the Bayesian approach was chosen for hyperparameter tuning across the three machine learning methods. This is also in line with the findings of Dang et al. (2024) and Quan (2024), where Bayesian optimization yielded better MSE, and computational efficiency compared to the grid search method.

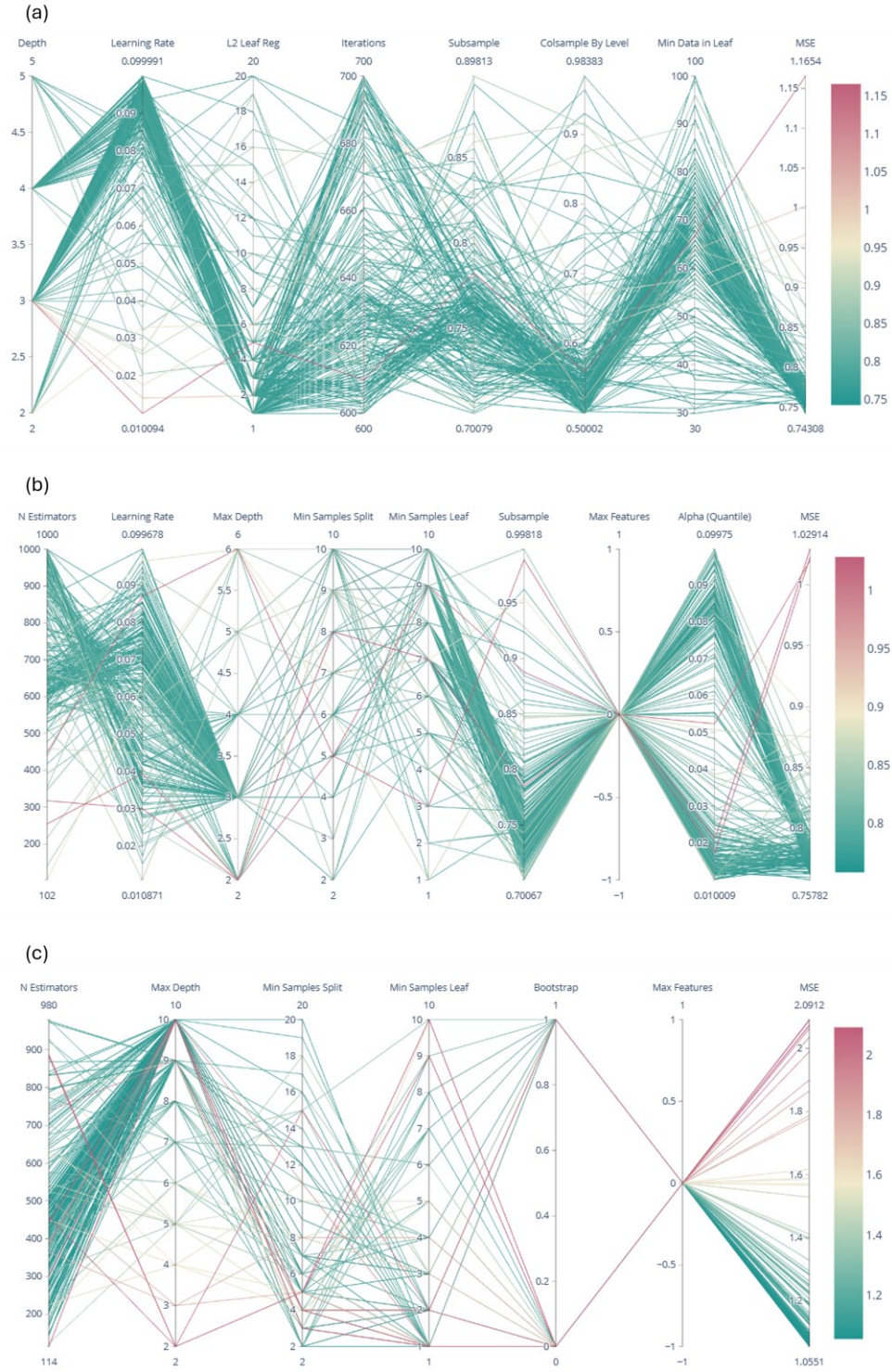


Figure 15. Progression of hyperparameter combinations and their corresponding average MSE values during the Bayesian optimization process with 200 iterations: (a) CatBoost, (b) Gradient Boosting, (c) Random Forest.

The Bayesian optimization process begins by randomly selecting an initial set of hyperparameters. The probability distribution from these initial values is then used to adjust the hyperparameters for each subsequent iteration until an optimal set is found. After several trials and adjustments, we used 200 iterations. Figure 15 shows the iteration process of Bayesian optimization for the three machine learning methods applied to shallow-crustal events. Results for Interface and Intralab events are provided in the appendix. As illustrated in the figure, the optimized hyperparameters progressively move towards lower values, resulting in the smallest MSE as the iterations continue.

Table 5. Hyperparameters and MSE values for three different algorithms

Algorithm	Hyperparameter	Shallow-crustal		Interface		Intralab	
		Value	MSE	Value	MSE	Value	MSE
Catboost	depth	3	0.7431	4	0.6913	4	0.7362
	learning_rate	0.093		0.0766		0.0989	
	l2_leaf_reg	4		1		1	
	iterations	700		732		692	
	subsample	0.8462		0.9842		0.8641	
	colsample_bylevel	0.5283		0.8359		0.9086	
	min_data_in_leaf	66		60		100	
Gradient-boosting	n_estimators	607	0.7578	474	0.7223	491	0.7441
	learning_rate	0.0705		0.0797		0.0837	
	max_depth	3		3		3	
	min_samples_split	10		10		8	
	min_samples_leaf	10		2		2	
	subsample	0.7333		0.8987		0.8343	
	alpha	0.0139		0.0584		0.0419	
Random Forest	n_estimators	427	1.0551	270	0.9958	400	1.1505
	max_depth	10		10		10	
	min_samples_split	5		4		4	
	min_samples_leaf	1		2		2	
	max_features	Sqrt		None		Log2	
	bootstrap	False		True		False	

Table 5 presents the hyperparameter values for the three machine learning methods across three tectonic settings, along with their performance. It can be observed that CatBoost achieves the smallest MSE among the three methods for all tectonic types. Based on these results, the CatBoost algorithm was selected for further study to construct the GMPM.

4.4. Models Evaluation

4.4.1. Models and assessment

Three machine learning-based models, utilizing the results of hyperparameter tuning, are compared with two traditional models: the modified existing GMPM and Zhao et al. (2006) model. The model by Zhao et al. (2006), denoted as the Zhao-06 is included in the evaluation process because it is the model used by BMKG to generate ShakeMaps for Indonesia (Irwandi et al., 2018; Muzli et al., 2018). The testing dataset is used for the comparative study. The comparison method involves examining the residual change with magnitude and epicentral distance, as well as the probability density function of the residuals. Additionally, metrics such as MSE, Pearson correlation coefficient, R^2 , and standard deviation of the residual are used to evaluate the predictive performance of the five models.

4.4.2. Residual analysis

Residual analysis was performed for three machine learning models and two traditional models by examining residuals against predicted values, analyzing changes in residuals with magnitude and epicentral distance, and using probability density function plots. Figure 16 illustrates the distribution of residuals against predicted values for all five models across three tectonic settings. The three machine learning-based models and the modified

traditional approach demonstrate randomly scattered, symmetrically distributed residuals without any discernible patterns, indicating that these models adequately capture the variability in the data. In contrast, the Zhao-06 model exhibits an asymmetrical residual distribution, predominantly in the negative range, indicating that the model overpredicts the observed values.

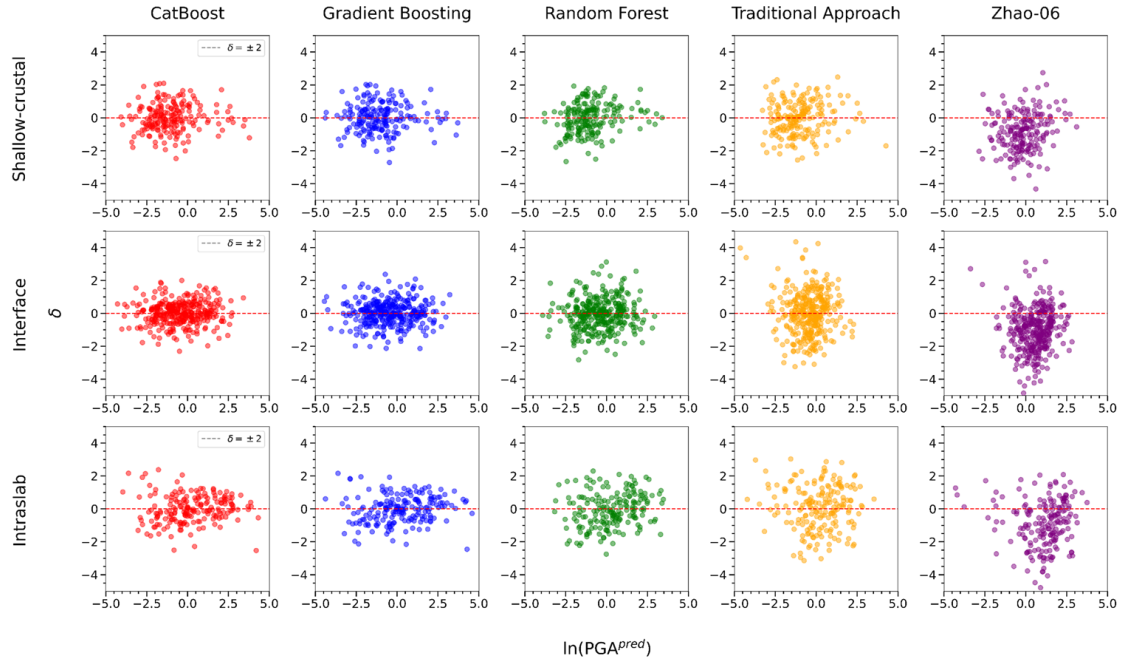


Figure 16. Residual versus predicted value plots for five models across three tectonic settings.

Figures 17 and 18 show the residual change plots against magnitude and distance, respectively. Visually, for all three tectonic types, the residual distribution for the three machine learning models is more concentrated around a residual value of 0. In contrast, the residuals for the two traditional approaches are more spread out. For the shallow crustal events, the residual distribution between $[-2, 2]$ is 97.44%, 97.95%, 98.46%, 95.90%, and 83.08%, and the residuals between $[-1, 1]$ are 75.90%, 74.87%, 72.31%, 64.62%, and

49.23% for Categorical Boosting (CB), Gradient Boosting (GB), Random Forest (RF), traditional approaches, and Zhao-06, respectively.

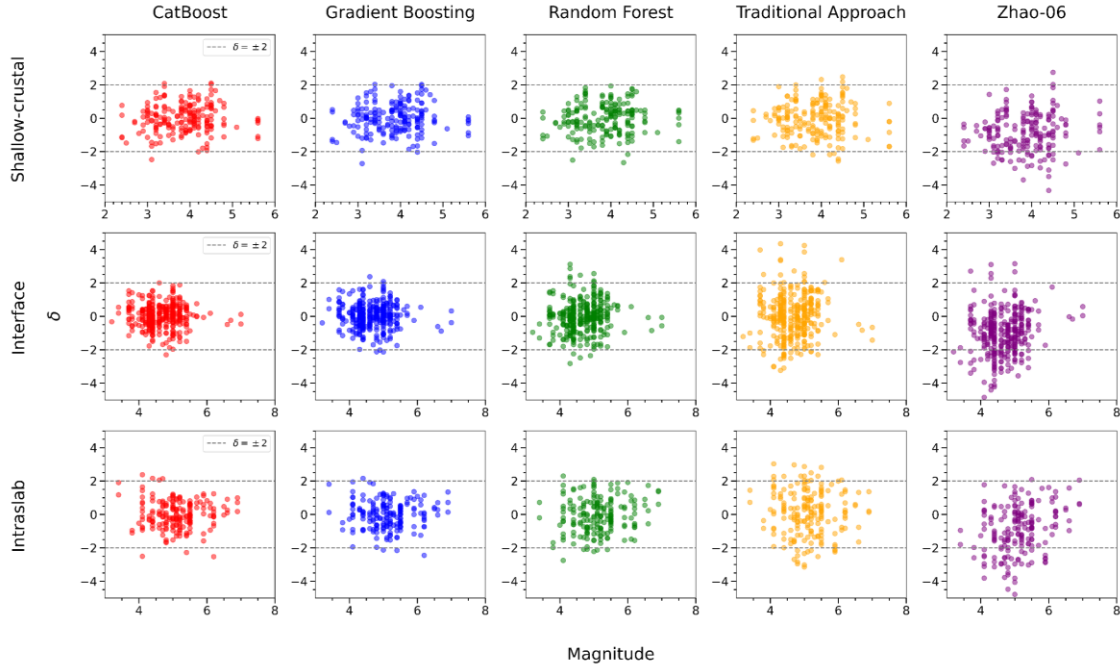


Figure 17. The residual changes with the Moment Magnitude (Mw) of five prediction models across three tectonic categories using the testing dataset.

For the interface events, the residual distribution between $[-2, 2]$ is 99.41%, 98.52%, 96.45%, 89.35%, and 75.15%, and the residuals between $[-1, 1]$ are 84.62%, 84.32%, 73.08%, 57.40%, and 46.75% for CB, GB, RF, traditional approaches, and Zhao-06, respectively. For the Intraslab events, the residual distribution between $[-2, 2]$ is 96.82%, 97.87%, 95.74%, 85.11%, and 77.13%, and the residuals between $[-1, 1]$ are 79.26%, 77.66%, 65.43%, 49.47%, and 47.34% for CB, GB, RF, traditional approaches, and Zhao-06, respectively. The results show that the three machine learning models outperform the two traditional approaches in terms of accuracy and consistency across different ranges of moment magnitude and epicentral distance. Among the machine learning models, CB demonstrates the best performance based on residual change analysis.

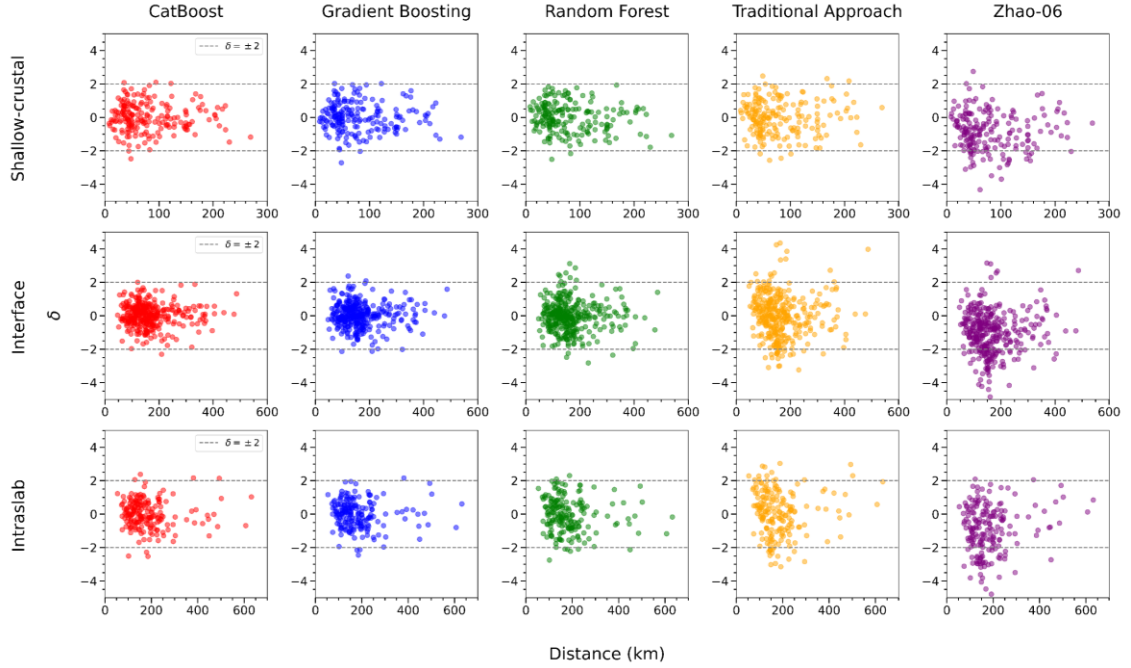


Figure 18. The residual changes with the epicentral distance (R_{epi}) of five prediction models across three tectonic categories using the testing dataset.

Figure 19 shows the probability distribution of the residuals. The three Machine Learning models and the modified traditional model exhibit a normal distribution with a mean of 0, indicating no systematic bias in their predictions. In contrast, the Zhao-06 model displays a right-skewed, suggesting that this model tends to overpredict the observed values. Furthermore, the residual distributions for the Categorical Boosting and Gradient Boosting (GB) models feature the narrowest and sharpest peaks, reflecting lower residual variance and more consistent predictions compared to the other models.

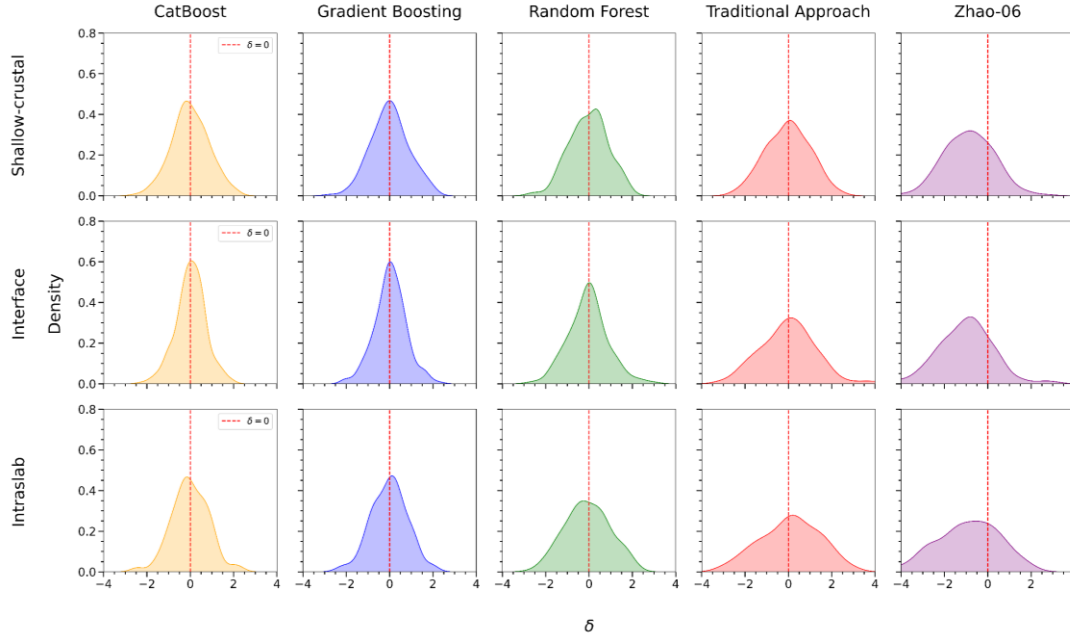


Figure 19. Kernel Density Estimate plots for the five models across the three tectonic categories using the testing dataset.

4.4.3. The assessment and comparison study of residuals

Another way to assess the performance of all models is by examining the evaluation metrics. Figure 20 shows the comparison of R, MSE, standard deviation, and R^2 values among the models across three tectonic settings. ML-based models perform better than traditional models. Among the five models evaluated, CB stands out as the best model for estimating ground motion from Shallow-crustal, Interface, and Intraslab earthquakes in West Java. For R and R^2 values across the three tectonic types, CB consistently has the highest scores. Furthermore, for MSE and standard deviation, the CB-based model achieves the lowest values among the five models.

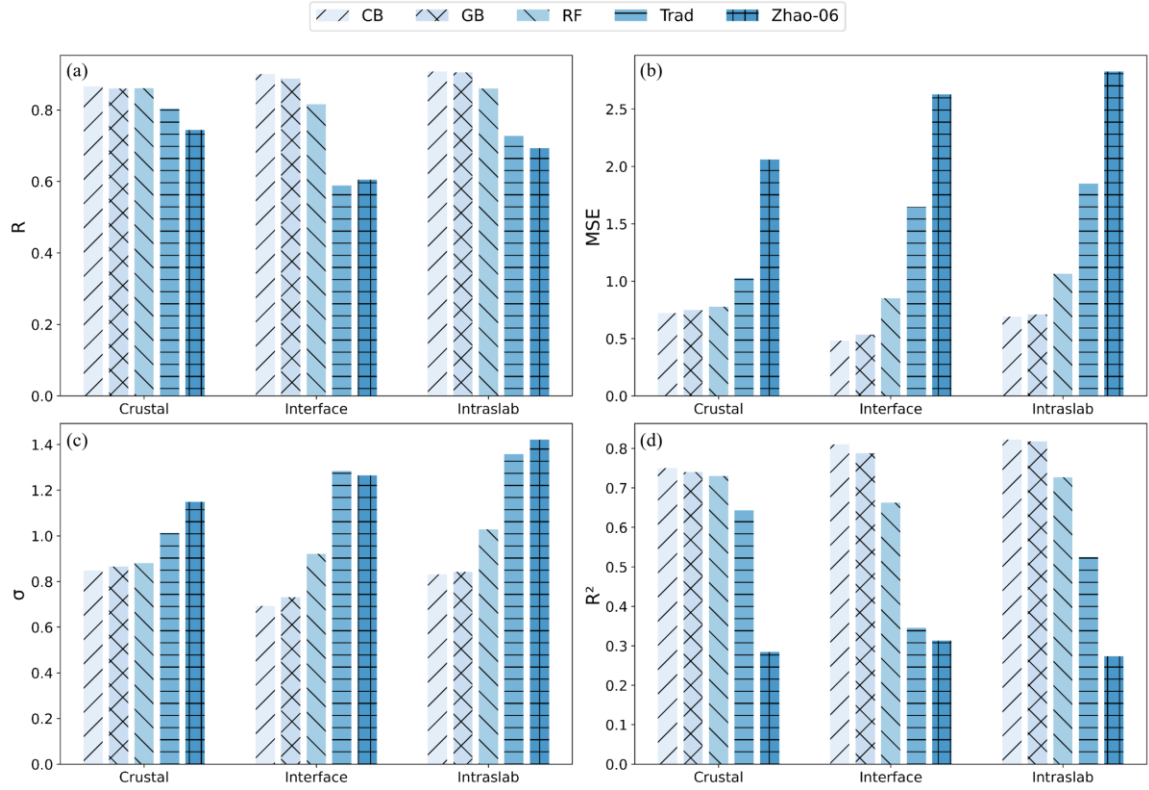


Figure 20. Comparison of results across all tectonic categories using CB, GB, RF, the modified traditional approach, and Zhao-06: (a) Pearson correlation coefficient, (b) Mean Squared Error, (c) Standard Deviation, and (d) Coefficient of Determination.

Figure 21 illustrates the comparison between $\ln(\text{PGA}_{\text{obs}})$ and $\ln(\text{PGA}_{\text{pred}})$ estimated by five models for shallow-crustal, interface, and intralab events. The results from the two traditional plots show significant scatter across all tectonic types. Additionally, the Zhao-06 model tends to over-predict at mid-to-low PGA levels, as shown in Figures 23e, 23j, and 23o. On the other hand, the three machine learning-based models demonstrate better performance with a smaller scatter. The CatBoost model exhibits the smallest scatter and low bias at both the highest and lowest PGA levels.

The R-values for the shallow-crustal events for the CatBoost (CB), Gradient Boosting (GB), Random Forest (RF), modified-traditional model, and Zhao-06 are 0.87, 0.86, 0.86, 0.80, and 0.74, respectively. For the Interface events, the R-values are 0.90, 0.89, 0.82, 0.80, and 0.74, respectively.

0.59, and 0.61 for the same models. Similarly, for Intraslab events, the R-values are 0.91, 0.90, 0.86, 0.73, and 0.69. According to the general hypothesis by Smith (1986), R-values above 0.8 indicate a strong positive correlation between observed and predicted values. Therefore, the highest R-value suggests that the CatBoost-based model outperforms the others.

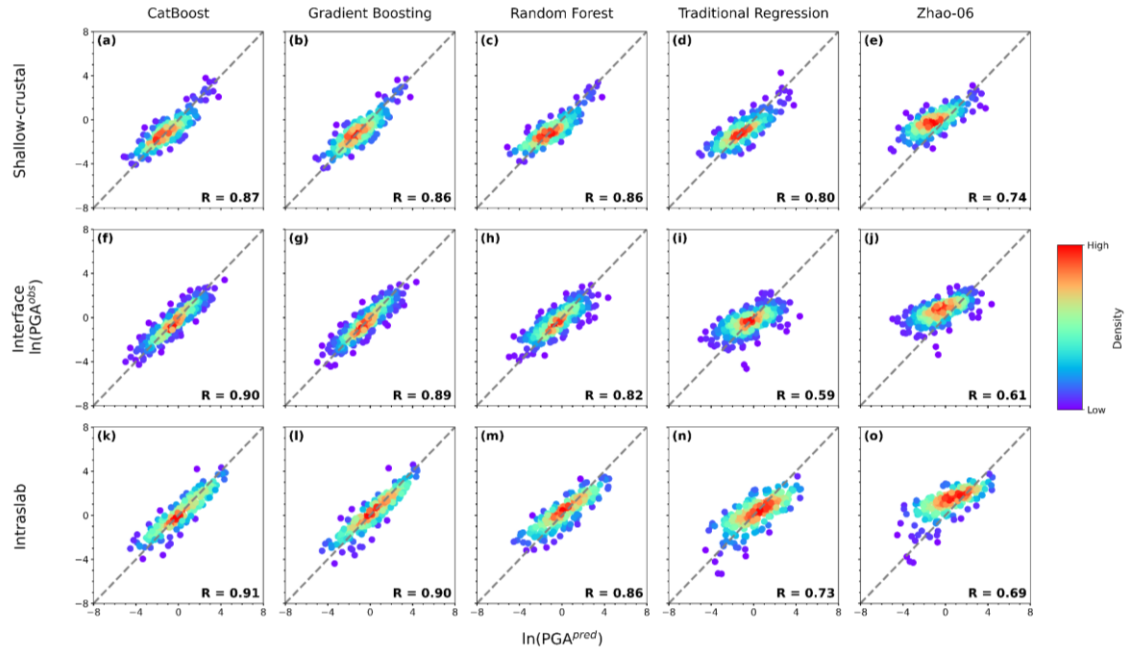


Figure 21. Natural logarithm of the PGA^{obs} versus those estimated by Catboost, GB, RF, Modified Traditional approach, and Zhao-06 models for three tectonic settings.

Figure 21 shows that the prediction model for shallow-crustal has lower accuracy than interface and intraslab. This could be due to the earthquake data used to develop the shallow-crustal model coming from several active faults in the West Java region such as Cimandiri, Lembang, Baribis, Cipamingkis and Garut (Supendi et al., 2018; Widiyantoro et al., 2022). These faults have different characteristics in terms of length, depth, type of fault, slip rate, strike, and dip of the fault, resulting in varying ground motion values. Therefore, with increased strong ground motion recordings for each fault, GMPMs can be

developed specifically for each fault, resulting in more accurate predictions. In addition to those factors, the radiation pattern effect also influences ground motion values for shallow-crustal earthquakes, especially in events with small to moderate magnitudes (Huang et al., 2023). Another factor affecting ground motion from shallow-crustal events is the local underground structure. Large underground structures can significantly impact seismic wave propagation, thereby affecting the seismic response of the soil and aboveground structures (Cheng et al., 2023; Pitilakis and Tsinidis, 2014).

Based on the residual analysis and the metric evaluation comparison, it can be concluded that the CB-based model consistently outperforms the other models across all three tectonic categories. This model will be used to determine the feature's importance and for further validation using recent earthquakes from 2024.

4.5. Proposed Model Explanation

4.5.1. Model performance analysis

As explained above, the CatBoost model performs better than the two other ensemble ML methods and the two traditional approach models. It is essential to check whether the CB-based model is overfitted to ensure that it generalizes well to unseen data and can reliably predict future earthquake events. An overfitted model indicates its weakness in predicting future earthquakes, as it captures specific patterns and noise from the training data that do not apply to new data (Bindi et al., 2017).

Table 6 shows the comparison of R , R^2 , MSE, and standard deviation values for the training and testing datasets of the three machine-learning models for the Interface dataset. The difference in values between the training and testing datasets for the RF-based model is

larger than for the CB and GB models, indicating that the RF model is overfitted. In contrast, for the CB and GB-based models, although the R and R² values are lower and the MSE and standard deviation are higher for the testing dataset compared to the training dataset, the differences are not significant. It can be concluded that both the CB and GB models, especially the CB-based model, are not considered overfitted.

Table 6. Comparison of R, R², MSE, and standard deviation (σ) values for three machine learning models on the training and testing datasets for Interface events.

		R	R²	MSE	σ
Catboost	Training dataset	0.94	0.88	0.28	0.53
	Testing dataset	0.90	0.81	0.47	0.69
GB	Training dataset	0.94	0.89	0.28	0.53
	Testing dataset	0.89	0.79	0.53	0.73
RF	Training dataset	0.92	0.92	0.41	0.64
	Testing dataset	0.82	0.66	0.85	0.92

Because the distribution of PGA values in the data used in this study is relatively varied, they are divided into several intervals for assessment. Three ranges were chosen: (0–10gal, 10–100gal, and 100–1000gal) for the comparative study. Pearson Correlation was used as the evaluation metric to assess the performance of the selected model, CatBoost, as shown in Figure 22.

As shown in the figure, for the 0–10-gal PGA range, the R values for all three tectonic types are excellent, consistently above 0.9. However, for the 10–100-gal range and values above 100 gal, the R values are significantly lower. This is due to the varying number of records across different PGA ranges. In summary, the CatBoost model performs well in the lower PGA range because of the larger amount of data available for all three tectonic types. However, its performance is weaker for mid and high PGA values, as there is less

data in these ranges. To enhance performance, the model should be updated as more data for mid and high PGA values becomes available.

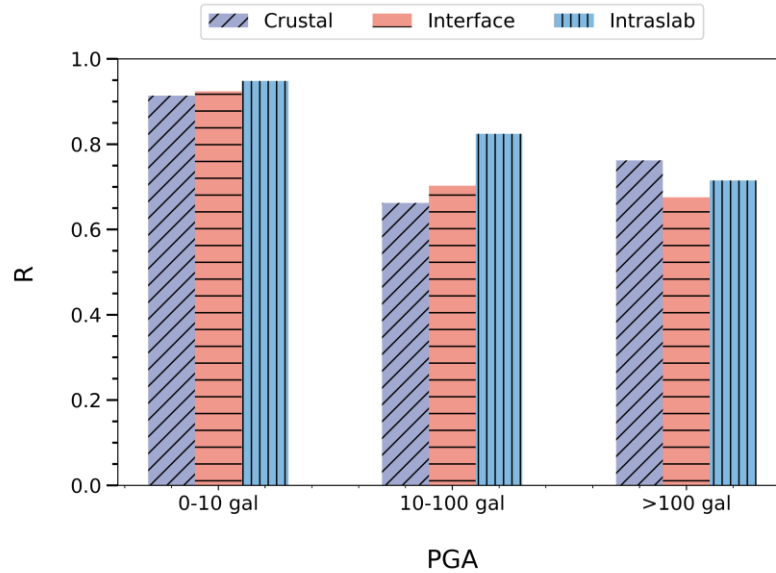


Figure 22. Comparison of R-value for different PGA range values and different tectonic settings.

4.5.2. SHAP value for feature parameters

Furthermore, one drawback of machine learning models is their "black-box" nature, which makes it challenging to understand their internal workings. In this study, the SHAP (SHapley Additive exPlanations) approach proposed by Lundberg & Lee (2017) is used to explain the proposed GMPMs. Figure 23 illustrates the SHAP values for all features of the CatBoost model across all tectonic types. The color represents the feature parameter values, with red indicating higher values and blue indicating lower values. Positive or negative SHAP values signify the corresponding positive or negative contributions to the predicted results.

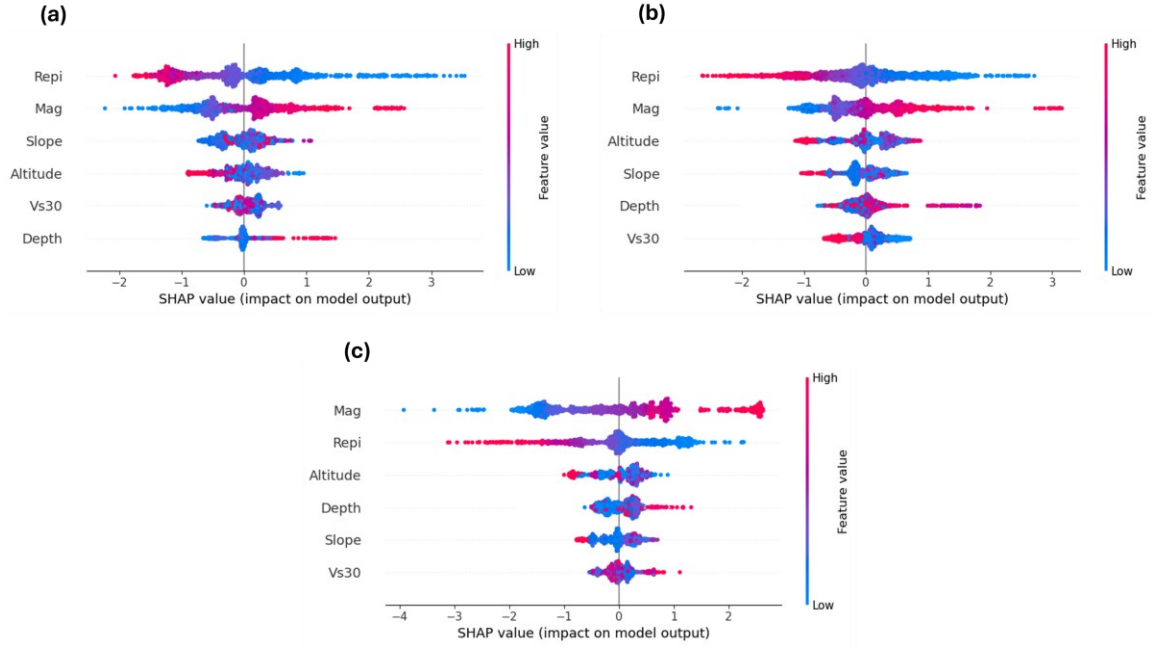


Figure 23. SHAP value for all explanatory variables for three tectonic types: (a) Shallow crustal, (b) Interface, (c) Intralab.

From the analysis of the combination of feature parameters and their respective SHAP values, it can be concluded that:

1. The SHAP value for Repi and Magnitude is significantly larger than the other four predictor variables for all tectonic types. The SHAP value increases as the Magnitude value becomes larger, indicating a positive contribution to the prediction results of PGA. In contrast, a large Repi value results in a small SHAP value, indicating a negative contribution to the prediction of PGA. These findings align with the trends in traditional GMPMs.
2. The SHAP value for depth increases as depth increases, suggesting that deeper earthquakes have a larger impact. This is because most of the records in this study are from the far field, where deeper earthquakes tend to have a more significant effect on sites, assuming other feature parameters remain constant.

3. The Vs30 parameter, which represents site effects, generally does not have a significant impact on predicting PGA. However, when Vs30 values are low, the SHAP values increase significantly, indicating a negative contribution. This aligns with domain knowledge, as low Vs30 values typically represent soil sites, which can amplify seismic waves and increase ground motion. These findings are consistent with the SHAP analysis results from Seo et al. (2022), Wang et al. (2023) Dang et al. (2024).
4. The SHAP values for slope and altitude do not exhibit a unilateral trend, as their correlation with the prediction can be both positive and negative.

The low importance of Vs30 in this study may be because much of the data used did not come from direct measurements, such as MASW or borehole data. In the study by Seo et al. (2022), they used Vs30 data obtained from MASW measurements, showing that Vs30 was the third most influential parameter in predicting ground motion after epicentral distance and magnitude for the South Korean region. Similarly, Dang et al. (2024) found through feature importance analysis that Vs30 was the third most influential factor in predicting ground motion for crustal earthquakes in Japan, using borehole data to determine Vs30 values. In the study by Wang et al. (2023), Vs30 emerged as the most influential parameter for predicting ground motion, with borehole data used to capture local site conditions. Given these findings, conducting research in Indonesia to obtain accurate Vs30 values through direct measurements is essential to improve ground motion predictions. Vs30 values obtained from direct measurements will also be useful in developing prediction models for PGV in the Indonesian region in the future. Research by K. Liu et al.

(2013) and Johnson et al. (2020) shows that PGV is more significantly influenced by the Vs30 value than PGA.

4.5.3. Interdependence of feature parameters

The interdependence of independent variables can be used to assess the model from multiple dimensions. In this study, two key variables—epicentral distance and magnitude—were analyzed to explore their interdependence and impact across three tectonic settings: shallow crustal, interface, and intraslab. Figure 24 illustrates how SHAP values change with epicentral distance and magnitude for each tectonic type. The results indicate that magnitude influences the contribution of epicentral distance to prediction results, with this trend consistent across all tectonic settings. However, differences emerge in how SHAP values decrease for each tectonic type.

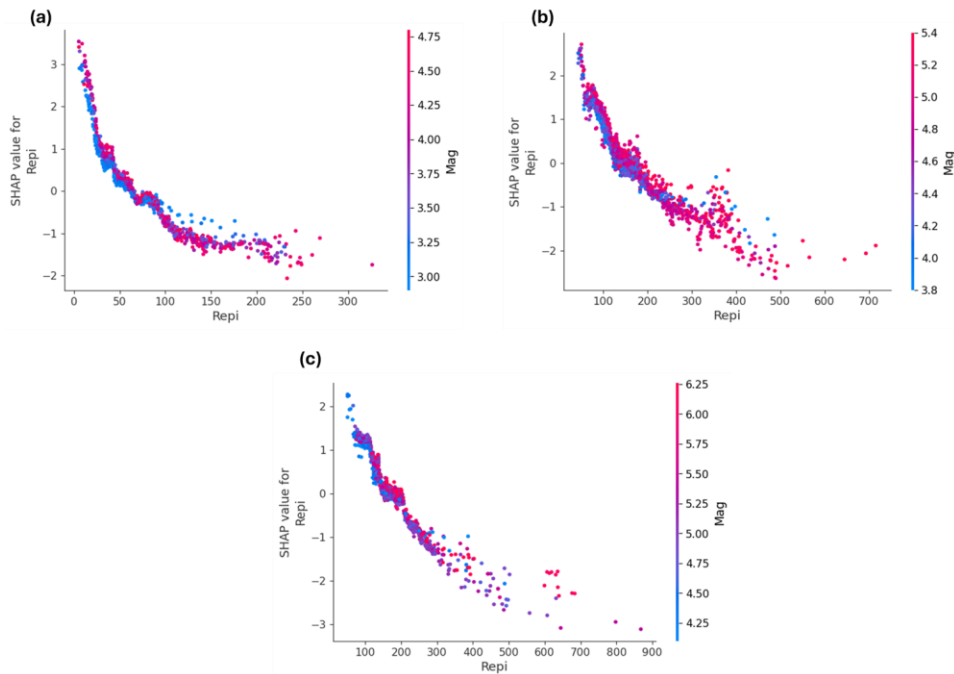


Figure 24. SHAP value for epicentral distance with changes of magnitude for three tectonic settings: (a) Shallow crustal, (b) Interface, and (c) Intraslab

For shallow crustal events, SHAP values decrease significantly at epicentral distances less than 50 km, with magnitude showing a positive impact on predictions within this range. Beyond 50 km, the decrease in SHAP values slows, and they eventually become negative, indicating a negative contribution to prediction results even for large-magnitude earthquakes. For interface events, SHAP values drop rapidly for epicentral distances less than 150 km and become negative at greater distances. Similarly, in intraslab events, SHAP values decrease rapidly for distances shorter than 200 km before turning negative.

These findings highlight differences in attenuation rates across tectonic settings. The rapid attenuation observed for shallow crustal events aligns with findings by Youngs et al. (1997) and Zhao et al. (2016), which reported faster attenuation rates in shallow crustal settings compared to subduction zones. Additionally, interface attenuation rates are faster than those for intraslab earthquakes. These observations underscore the strong influence of tectonic setting on ground motion behavior and its contributing factors.

Based on Figure 23, which illustrates the impact of six predictor variables on prediction results, and Figure 24, which shows the combined contribution of the two most impactful variables, the CatBoost model's predictions align with commonly understood domain knowledge. For instance, there is a positive correlation between ground motion and magnitude for a given epicentral distance, consistent with established principles. This analysis confirms that the CatBoost model's predictions are reasonable and demonstrate good accuracy.

4.6. Validation using recent Earthquake

As noted earlier, the Catboost-based models have proven the best and are selected as the GMPMs for our research area. In addition to using test data, we test the performance of the

selected model with datasets not included in the training or testing process. I used three earthquake events that occurred in 2024: the M 3.4 earthquake on July 5, 2024, and the M 2.5 earthquake on July 8, 2024, which were used to validate the model developed for crustal events. Meanwhile, I chose the M 4.9 earthquake from April 22, 2024, to validate the Interface model. Unfortunately, I could not validate the intraslab model as there were no Intraslab earthquakes in 2024.

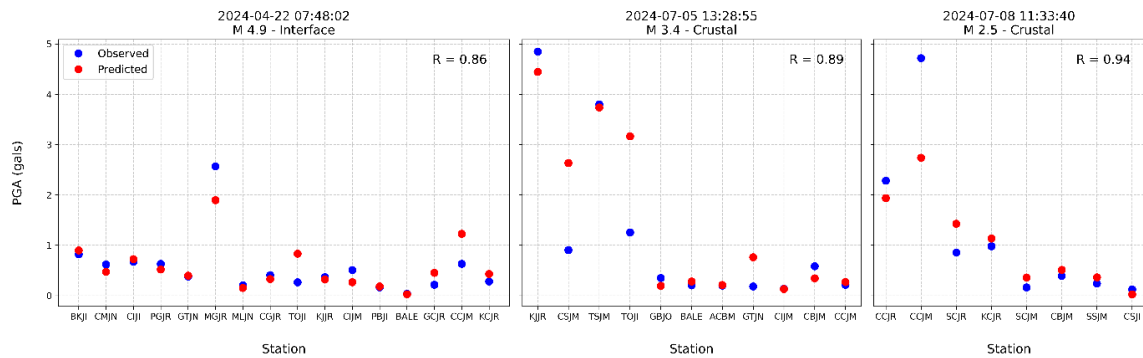


Figure 25. Observed vs Predicted plot for three recent earthquakes using Catboost-based model

Figure 25 shows the observation and prediction plots for each recording station from the GB-based model for the three recent earthquakes. Based on the general hypothesis by Smith (1986), the obtained R-value for three events above 0.8 indicates a strong positive correlation between the observed and predicted values. This suggests that the model can accurately predict ground motion values even when using new data.

It should be noted that the prediction results of statistical methods can only be relied on within the limits of the data used in the training process (Khosravikia and Clayton, 2021). And statistical methods including machine learning are trained using a specific database that limits the ability to predict values outside the training dataset range. Therefore, GMPMs must always be updated by increasing the size and diversity of training datasets,

particularly for underrepresented magnitude ranges. Additionally, incorporating more geophysical variables, such as fault mechanism, radiation pattern and directivity, and information about the local underground structure will enhance model robustness and accuracy. Lastly, continuous model validation using recent earthquake data and real-time updates will ensure that the models remain relevant and accurate.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

GMPMs have been developed for three types of earthquake sources (crustal, interface, and intraslab) in the West Java region to support the Earthquake Early Warning system. I used 3561 Peak Ground Acceleration recordings from 381 earthquakes recorded between 2010 and 2023 by 60 BMKG accelerometer stations in West Java, with magnitudes ranging from 2.3 to 7. The dataset was divided into 80% for training and 20% for testing. I evaluated three machine learning algorithms: CB, GB, and RF, along with the Optuna Bayesian optimization techniques to predict PGA values and compared these results to the classical approach and model by Zhao et al. (2006). Six explanatory variables are considered: moment magnitude, epicentral distance, depth, Vs30, slope, and site altitude, with the target variable being the geometric mean of the natural logarithm of PGA.

To evaluate the performance of each model, I used quantitative metrics such as Pearson correlation coefficient, Coefficient of Determination, MSE, and standard deviation along with residual analysis. The comparative study using those evaluation metrics showed that all machine-learning models outperformed the traditional approach and model by Zhao et al. (2006). CB-based model demonstrating the best performance across all types of earthquakes. Residual analysis emphasizes the superiority of the CB-based model, as its residuals were randomly distributed along the $\delta = 0$ line. Additionally, the KDE plot indicated normal distribution with 0 average.

The selected CB-based model was evaluated using three recent earthquakes from 2024, which were not part of the training or testing dataset. The results showed that the predicted ground motion values closely matched the observed values. To understand the working process of the selected model, I employed SHAP (SHapley Additive exPlanations). I found the epicentral distance (R_{epi}) and Moment Magnitude (M_w) were the most influential variables in predicting PGA for the three types of earthquakes, while V_{s30} had the least influence among the six independent variables. Given its strong performance, the CB-based model is expected to enhance the prediction of PGA values within the developing Earthquake Early Warning System in Indonesia, potentially reducing casualties in the event of a major earthquake.

5.2. Recommendations

Based on the conclusions of the study, the following recommendations can be made for future research:

1. Updating GMPMs

GMPMs must always be updated by increasing the size and diversity of training datasets, particularly for underrepresented magnitude ranges.

2. Incorporating Geophysical Variables

Incorporating more geophysical variables, such as fault mechanism and directivity, will improve model accuracy, especially for shallow crustal models.

3. Obtaining Accurate Vs30 Values

Conducting research in Indonesia to obtain accurate Vs30 values through direct measurements is essential to improve ground motion predictions.

4. Developing Additional Ground Motion Parameters

Developing additional ground motion parameters, such as Peak Ground Velocity (PGV) and Spectral Acceleration, is essential before the Earthquake Early Warning System (EEWS) can be implemented more widely.

5. Sensor Location Optimization for Uncertainty Reduction

Future research should focus on optimizing the sensor locations to reduce uncertainty in predictions. By strategically placing sensors, prediction accuracy can be improved while reducing the costs associated with the number of sensors needed to achieve equally informative results.

APPENDIX

Table 7. Local site conditions in accelerograph sensors used in this study

Code	Lat	Long	V_{s30} (m/s)	Slope (o)	Altitude (m)	NEHRP	
						Site Class	Description
ACJM	-6.80	108.62	264.58	6.65	10.82	D	Stiff Soil
BACE	-6.88	107.60	403.15	6.92	789.58	C	Soft Rock
BALE	-6.83	107.62	611.31	28.84	1260.29	C	Soft Rock
BKJI	-7.36	108.53	289.09	5.70	30.63	D	Stiff Soil
CBJI	-6.70	106.93	574.17	11.08	975.60	C	Soft Rock
CBJM	-6.57	107.21	900.00	19.46	672.23	B	Rock
CBJN	-6.73	108.53	283.14	1.34	17.76	D	Stiff Soil
CBJR	-6.73	107.44	369.48	10.91	616.68	C	Soft Rock
CCJM	-7.02	107.14	553.52	9.00	1016.82	C	Soft Rock
CCJR	-7.00	107.14	551.50	8.65	991.54	C	Soft Rock
CGJR	-7.52	107.49	437.90	5.07	43.31	C	Soft Rock
CIJI	-7.32	108.20	295.32	6.81	378.51	D	Stiff Soil
CIJM	-6.49	108.19	226.02	1.94	9.96	D	Stiff Soil
CMJI	-7.78	108.45	323.85	5.10	45.22	D	Stiff Soil
CMJN	-7.33	108.36	342.34	2.04	189.82	D	Stiff Soil
CNJI	-7.31	107.13	498.40	4.78	556.85	C	Soft Rock
CSJI	-7.33	106.52	326.29	0.21	102.38	D	Stiff Soil
CSJM	-6.74	108.01	541.37	1.61	355.44	C	Soft Rock
CSJR	-6.97	106.82	330.56	3.56	363.12	D	Stiff Soil
CWJM	-6.74	107.44	429.91	14.82	632.44	C	Soft Rock
DBJI	-6.55	106.74	291.32	8.91	174.11	D	Stiff Soil
DSJR	-6.85	106.92	580.38	13.35	956.04	C	Soft Rock
ESJR	-7.23	106.52	422.70	2.19	316.85	C	Soft Rock
GBJO	-6.83	107.63	592.59	10.68	1283.04	C	Soft Rock
GBJR	-6.64	106.68	530.81	4.58	482.06	C	Soft Rock
GCJR	-7.21	107.14	536.96	7.31	377.02	C	Soft Rock
GTJN	-7.22	107.90	331.15	4.17	718.71	D	Stiff Soil
JAUI	-6.37	106.83	265.91	5.33	76.35	D	Stiff Soil
JBJI	-6.48	106.47	351.67	5.37	103.50	D	Stiff Soil
JCJI	-6.73	108.26	231.80	3.51	43.30	D	Stiff Soil
JPJI	-6.53	107.42	371.02	3.63	113.43	C	Soft Rock
JSJR	-7.26	106.63	369.49	1.29	320.83	C	Soft Rock
JTJM	-7.06	106.80	341.51	3.03	505.73	D	Stiff Soil
KCJR	-6.91	107.11	618.81	20.25	617.54	C	Soft Rock
KJJR	-6.86	107.92	472.49	9.78	458.01	C	Soft Rock

KKJN	-6.98	108.48	482.48	5.47	499.05	C	Soft Rock
KSJR	-6.83	106.66	329.50	2.97	638.71	D	Stiff Soil
LCJR	-6.87	107.16	341.39	6.42	399.40	D	Stiff Soil
LPJR	-7.50	108.40	384.36	4.41	540.43	C	Soft Rock
LSJR	-7.13	106.69	385.74	2.27	591.74	C	Soft Rock
MGJR	-7.41	107.69	555.64	7.97	735.94	C	Soft Rock
MLJN	-6.84	108.24	398.61	2.97	150.40	C	Soft Rock
PBJI	-7.09	107.48	440.30	11.15	1051.91	C	Soft Rock
PCJM	-6.91	108.71	215.95	3.85	23.35	D	Stiff Soil
PCJR	-7.68	108.65	187.96	2.71	4.31	D	Stiff Soil
PGJR	-7.65	107.73	262.91	0.67	14.04	D	Stiff Soil
PKJM	-6.80	108.44	522.10	13.82	265.61	C	Soft Rock
PSJM	-6.97	106.55	583.06	6.09	182.68	C	Soft Rock
RSJR	-7.33	106.52	326.29	0.83	100.63	D	Stiff Soil
SCJM	-6.84	107.22	295.97	11.32	302.25	D	Stiff Soil
SCJR	-7.10	107.13	398.61	3.22	867.06	C	Soft Rock
SEJM	-6.86	108.59	431.37	4.70	133.14	C	Soft Rock
SKJI	-7.01	106.56	704.27	23.51	74.87	C	Soft Rock
SSJM	-6.89	106.96	522.52	9.01	826.93	C	Soft Rock
SSJR	-7.21	106.88	409.71	4.48	376.65	C	Soft Rock
TOJI	-6.76	108.13	300.40	0.70	38.87	D	Stiff Soil
TSJM	-6.73	107.81	437.05	3.37	397.74	C	Soft Rock
TSJN	-7.32	108.22	281.15	0.51	352.78	D	Stiff Soil
TSJR	-7.42	106.72	270.90	6.06	5.60	D	Stiff Soil
WSJM	-6.97	106.72	378.02	8.93	286.51	C	Soft Rock
SPSJM	-6.67	107.61	497.13	1.83	638.79	C	Soft Rock

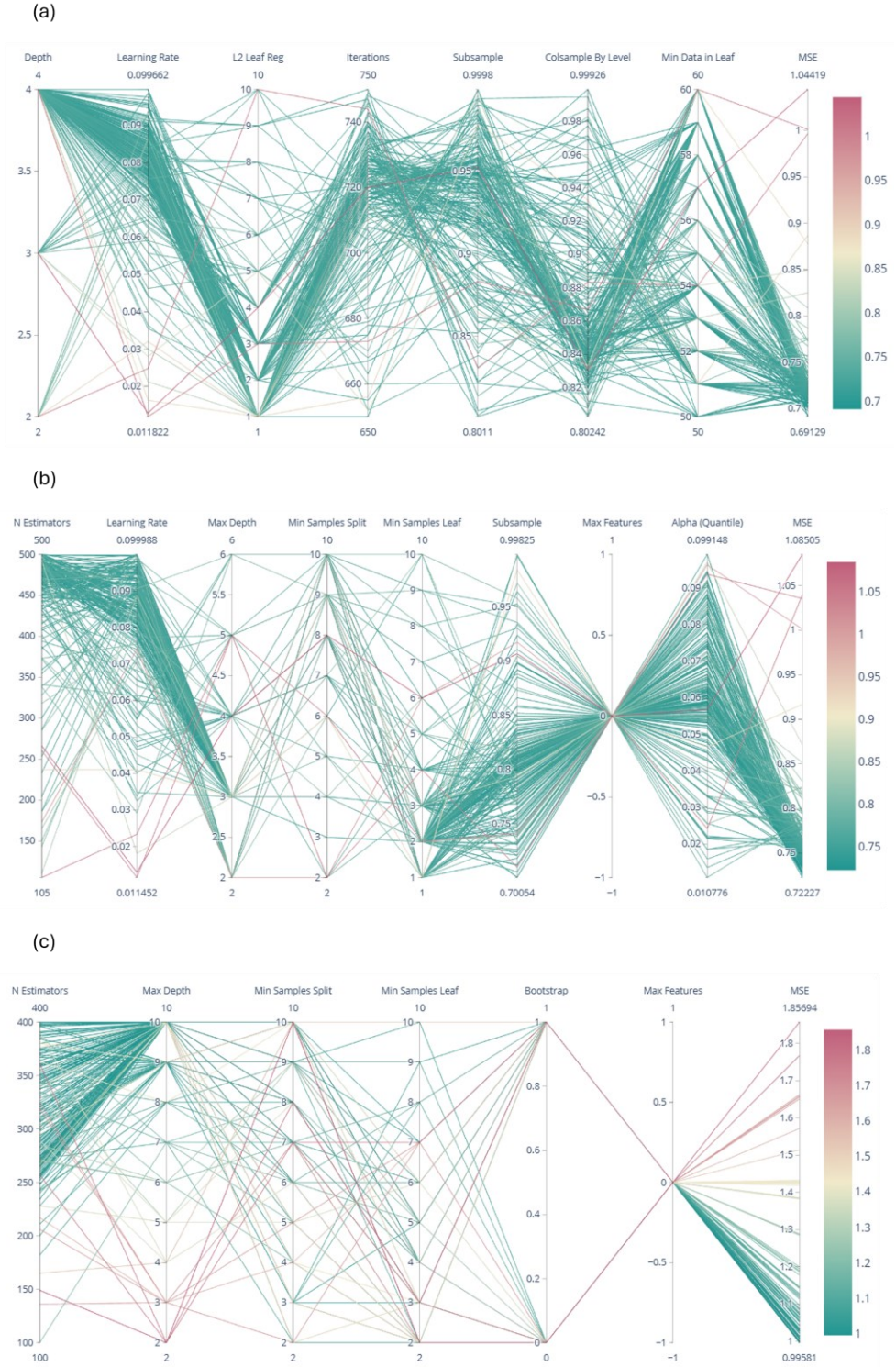
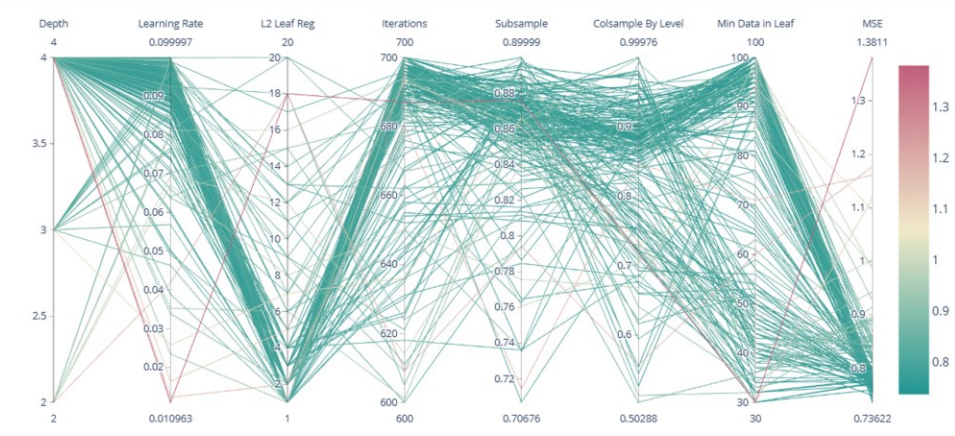
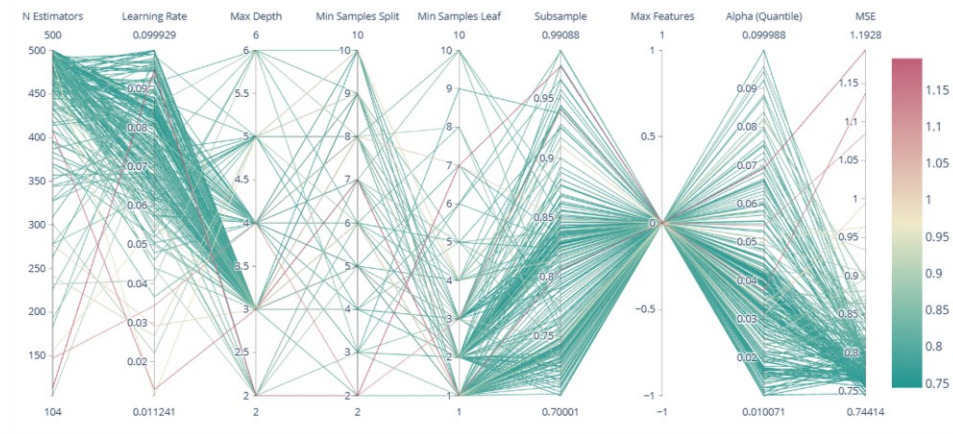


Figure 26. Progression of hyperparameter combinations and their corresponding average MSE values during the Bayesian optimization process with 200 iterations: (a) CatBoost, (b) Gradient Boosting, (c) Random Forest for Interface events.

(a)



(b)



(c)

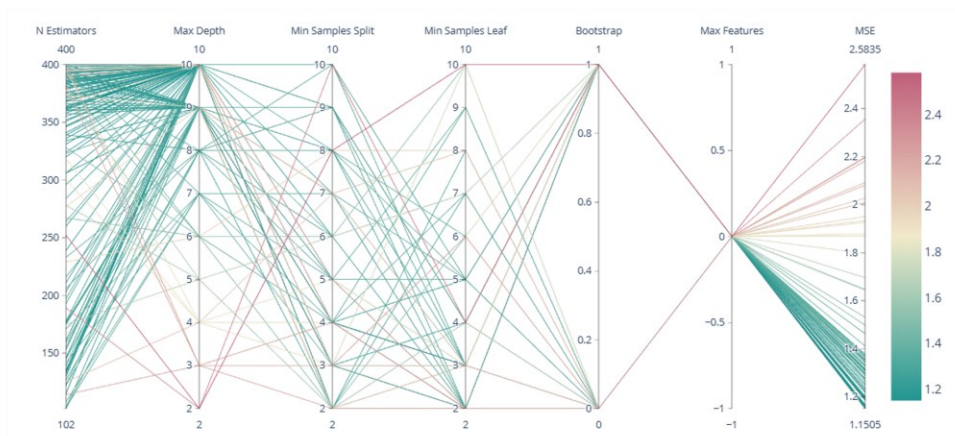


Figure 27. Progression of hyperparameter combinations and their corresponding average MSE values during the Bayesian optimization process with 200 iterations: (a) CatBoost, (b) Gradient Boosting, (c) Random Forest for Intralab events.

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