International Journal of Advances in Data and Information Systems
Vol. 7, No. 1, April 2026, pp. 370~378
ISSN: 2721-3056, DOI: 10.59395/ijadis.v7i1.1400

Deep Learning Approach for Earthquake Detection and Classification using MobileNet V2 Transfer Learning

Giel Utami Putri Siregar[1], Agus Subekti[2], Hasri Akbar Awal Rozaq[3], Oktay Yıldız[4]
[12]Faculty of Information Technology, Universitas Nusa Mandiri, Jakarta, Indonesia
[3]Graduate School of Informatics, Department of Computer Science, Gazi University, Ankara, Türkiye
[4]Faculty of Engineering, Department of Computer Engineering, Gazi University, Ankara, Türkiye
[1]14220033@nusamandiri.ac.id, [2]agussubekti@nusamandiri.ac.id, [3]hakbar.rozaq@gazi.edu.tr, [4]oyildiz@gazi.edu.tr

Article Info
Article history:
Received Jun 09, 2025
Revised Feb 08, 2026
Accepted Apr 08, 2026

Keywords:
Earthquake Detection
MobileNetV2
Spectrogram (STFT)
Seismic Time Series

ABSTRACT
Earthquake detection is a critical component of disaster management, as early identification of seismic events can help mitigate potential damage and support timely response efforts. This study evaluates the application of deep learning for binary earthquake detection using a lightweight Convolutional Neural Network (CNN) based on the MobileNetV2 architecture. The experiments were conducted using seismic waveform data from the Stanford Earthquake Dataset (STEAD), which were transformed into time–frequency representations through the Short-Time Fourier Transform (STFT). Spectrogram images derived from the seismic signals were used as input to the CNN models. Transfer learning was applied to MobileNetV2 to adapt the pretrained architecture to the earthquake detection task. The proposed approach achieved an accuracy of 99%, precision of 100%, recall of 97.96%, and an F1-score of 98.97% on the test dataset. In terms of model complexity, MobileNetV2 has 7,176,600 total parameters and 1,639,538 trainable parameters, indicating a favorable balance between performance and computational efficiency. For comparative evaluation, MobileNetV2 was benchmarked against several commonly used CNN architectures, including CNN Vanilla, MobileNetV1, VGG16, and ResNet, under the same experimental conditions. The results indicate that MobileNetV2 provides competitive detection performance while maintaining a significantly smaller model size. Although real-time deployment on mobile devices was not implemented in this study, the findings suggest that lightweight CNN architectures, such as MobileNetV2, hold promise for future earthquake detection systems operating in resource-constrained environments.

This is an open access article under the CC BY-SA license.

Corresponding Author:
Agus Subekti,
Faculty of Information Technology, Universitas Nusa Mandiri, Jakarta, Indonesia
Email: agussubekti@nusamandiri.ac.id

1. INTRODUCTION

Earthquake detection plays a crucial role in disaster mitigation, as timely identification of seismic events can significantly reduce potential damage and support effective evacuation planning [1]. Conventional earthquake monitoring systems often rely on manual analysis or specialized hardware, which may be costly, time-consuming, and limited in scalability [2]. Consequently, the development of automated and efficient earthquake detection techniques has become an important research focus, particularly for applications requiring real-time or near–real-time response [3].

Recent advances in deep learning have significantly influenced seismic signal analysis. In particular [4], Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in earthquake detection and magnitude estimation, thanks to their ability to learn complex patterns from seismic data [5], [6]. Previous studies have reported high detection accuracy using CNN-

based approaches; for example, deep residual networks combining CNN and recurrent units have achieved exceptionally high detection rates and robust performance in noisy environments [7], while generalized CNN models have been widely validated for seismic phase detection [8]. Additionally, attentive deep-learning models such as the Earthquake Transformer highlight the potential of attention mechanisms in enhancing detection performance [9]. These results highlight the potential of deep learning for reliable seismic event detection.

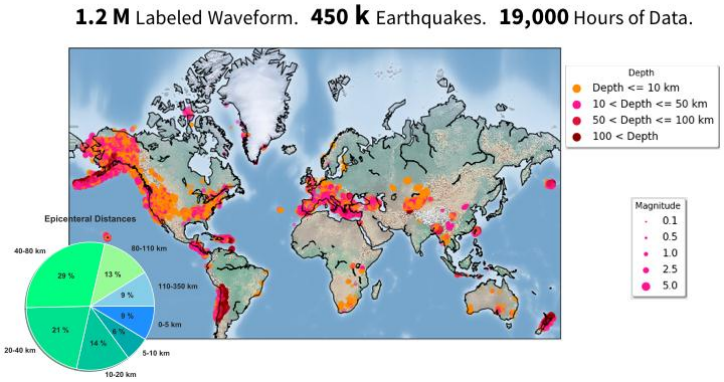


Fig. 1. Stanford Earthquake Dataset (STEAD)

Despite their high performance, many existing deep learning models for seismic analysis are computationally intensive and require substantial memory resources. Architectures such as VGG, ResNet, and other deep frameworks, while effective, are often impractical for deployment on resource-constrained platforms, including mobile and embedded devices [10], [11]. This limitation poses a challenge for extending earthquake detection capabilities to edge-based systems and low-cost monitoring infrastructures.

To address these constraints, lightweight CNN architectures have gained increasing attention. Among them, MobileNetV2 is specifically designed for efficient computation by employing depthwise separable convolutions, inverted residual blocks, and linear bottlenecks. These design choices substantially reduce the number of parameters and computational cost while maintaining competitive performance [12]. As a result, MobileNetV2 has been widely adopted in applications where efficiency and scalability are critical, making it a promising candidate for seismic signal classification on resource-limited platforms.

Several studies have explored alternative deep learning architectures for seismic applications. For example, hybrid CNN–LSTM models have been applied to earthquake magnitude estimation and binary classification tasks, emphasizing the importance of capturing both spatial and temporal features of seismic data [13], [14]. Other approaches have incorporated machine learning frameworks, such as Bayesian and feature optimization techniques, for magnitude estimation and seismic feature extraction [15]. While these methods demonstrate strong predictive performance, their computational demands often limit their applicability in real-time or mobile-based scenarios.

Building on these observations, this study focuses on the empirical evaluation of MobileNetV2 with transfer learning for binary earthquake detection using spectrogram representations derived from seismic waveform data. Rather than proposing a novel detection framework, the primary contribution of this work lies in systematically comparing MobileNetV2 with several commonly used CNN architectures under identical preprocessing and evaluation settings. By analyzing both classification performance and model complexity, this study aims to assess the suitability of lightweight CNN models for scalable and computationally efficient earthquake detection, particularly in environments with limited computational resources.

2. RESEARCH METHOD

2.1 Data and Materials

This study utilizes seismic waveform data for binary earthquake detection, classifying signals into two categories: earthquake and noise. The dataset employed is the Stanford Earthquake Dataset (STEAD), which comprises over 1 million three-component seismograms recorded

between 1984 and 2018 at seismic stations across multiple geographic regions. The dataset includes both earthquake events and non-earthquake noise signals, making it suitable for supervised classification tasks [4], [5].

Each seismic record contains three channels corresponding to the vertical (Z), north–south (N), and east–west (E) components. To convert the time-series data into a representation suitable for image-based deep learning models, the seismic signals were transformed into spectrogram images using the Short-Time Fourier Transform (STFT), a widely used time–frequency analysis technique in seismic signal processing and machine learning-based earthquake detection [1], [16].

For this study, a subset of 21,750 spectrogram images was selected and balanced evenly between the earthquake and noise classes to avoid class imbalance during training, a strategy commonly adopted to improve classification robustness in seismic datasets [7]. All images were normalized to a pixel intensity range of 0 to 1 to stabilize training and accelerate convergence of deep neural networks [17]. The dataset was randomly split into 80% for training, 10% for validation, and 10% for testing. This random split was applied without enforcing station-wise or region-wise separation; therefore, the evaluation primarily reflects within-distribution performance, as also reported in several previous deep-learning-based seismic classification studies [2], [8].

2.2 Methodology

Figure 3 illustrates the overall workflow of the proposed methodology, comprising four main stages: dataset preparation, spectrogram generation, transfer-learning-based model training, and model evaluation.

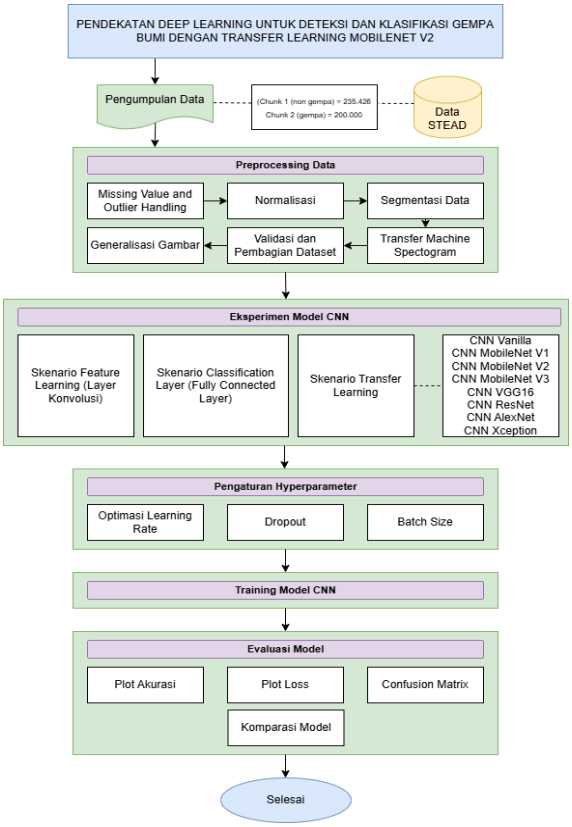


Fig. 3. Proposed Methodology

1) Dataset Collection and Preparation

Raw seismic waveform data were extracted from the Stanford Earthquake Dataset (STEAD) in three-channel format, consisting of vertical (Z), north–south (N), and east–west (E) components [4]. Each waveform was segmented into 60-second windows, a duration commonly adopted in seismic signal processing to capture complete event characteristics while maintaining

computational efficiency. Before transformation, each seismic signal was standardized to zero mean and unit variance to reduce scale variability and mitigate the influence of extreme amplitudes and background noise, as defined by

$$x_{\text{norm}}(t) = \frac{x(t) - \mu}{\sigma},$$

where μ and σ denote the mean and standard deviation of the signal, respectively [18]. This normalization step is widely used to stabilize deep neural network training and improve convergence behavior [19].

2) Spectrogram Generation and Data Augmentation

Each segmented waveform was transformed into a two-dimensional spectrogram using the Short-Time Fourier Transform (STFT), a standard time–frequency representation technique in seismic analysis and machine learning-based earthquake detection [20], [21]. The STFT of a discrete-time signal $x[n]$ is defined as

$$\text{STFT}(m,k) = \sum_{n=-\infty}^{\infty} x[n]\, w[n-m]\; e^{-j2\pi kn/N},$$

where $w[n]$ is a windowing function, m denotes the time index, and k represents the frequency bin [22].

In this study, a Hamming window of 256 samples was used with 50% overlap between adjacent windows and an FFT size of 512, a configuration shown to balance time and frequency resolution for seismic waveform analysis. The three seismic channels were combined by averaging their magnitude spectra, resulting in a single grayscale spectrogram for each seismic event. This channel-averaging approach preserves global time–frequency characteristics while maintaining a compact input representation suitable for lightweight CNN architectures [3].

All spectrograms were resized to 100×150pixels and stored in grayscale format. During training, data augmentation techniques—including horizontal shifting, slight rotation, zooming, and translation—were applied to enhance model robustness and reduce overfitting [23]. The final dataset was evenly balanced between earthquake and noise classes to prevent classification bias.

3) Model Training and Evaluation

Transfer learning was employed using the MobileNetV2 architecture pretrained on the ImageNet dataset [24], [25]. The pretrained convolutional base was retained, while the original classification head was replaced with a task-specific architecture consisting of a global average pooling layer, a dropout layer, and a dense output layer with softmax activation for binary classification. The softmax function is defined as

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}},$$

where C denotes the number of classes.

The model was trained using the Adam optimizer with a learning rate of 10^{-4}, which adaptively updates parameters according to first- and second-order moment estimates of the gradients [26]. The loss function used was categorical cross-entropy, defined as

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i),$$

where y_i and $\hat{y}_i$ represent the ground-truth and predicted class probabilities, respectively. Training was conducted for up to 30 epochs, with early stopping based on validation loss to prevent overfitting. For comparative evaluation, additional CNN architectures—including a vanilla CNN, MobileNetV1, VGG16, and ResNet50—were trained under identical preprocessing, training, and evaluation settings to ensure a fair comparison [27], [28].

4) Model Evaluation and Interpretability

Model evaluation focused on quantitative performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis [29], [30], which are standard measures for binary classification in seismic event detection. Training and validation accuracy–loss curves were examined to assess convergence behavior and generalization performance. To support model interpretability, gradient-based activation-mapping techniques were explored to visualize the time–frequency regions in spectrograms that contributed most strongly to model predictions. These visualization methods provide qualitative insights into the learned representations of deep CNNs applied to seismic data. However, interpretability analyses are presented as supplementary observations rather than primary contributions of this study.

3. RESULTS AND DISCUSSION

3.1 Earthquake Image Classification Using Deep Learning Models

This study evaluated the performance of multiple convolutional neural network (CNN) architectures—namely CNN Vanilla, MobileNet V1, MobileNet V2, MobileNet V3, VGG16, and ResNet—for binary earthquake detection, where seismic spectrogram images were classified into two categories: earthquake and noise. Each model was trained and evaluated under the same preprocessing and experimental setup to ensure a fair comparison. The performance of the models was assessed using accuracy, precision, recall, and F1-score. In addition, architectural complexity was analyzed in terms of total, trainable, non-trainable, and optimizer parameters. The comparative results are summarized in Table 1.

Table I. Performance Comparison of CNN Models for Earthquake Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Total Params	Trainable Params	Non-Trainable Params	Optimizer Params
CNN Vanilla	96	98,32	93,6	96	23.045.912	7.681.970	0	15.363.942
CNN MobileNet V1	98	100	97	98	5,591,576	787,570	3,228,864	1,575,142
CNN MobileNet V2	99	100	98	99	7,176,732	1,639,582	2,257,984	3,279,166
CNN MobileNet V3	96	100	91	95	6,686,168	1,229,938	2,996,352	2,459,878
CNN VGG16	98,4	98,36	98,36	98	15.897.752	394.354	14.714.688	788.71
CNN ResNet	96,8	95,38	98,41	96	31.455.448	2.622.578	23.587.712	5.245.158

Among the evaluated models, MobileNet V2 achieved the highest overall performance, with an accuracy of 99%, precision of 100%, recall of 98%, and an F1-score of 99%, while maintaining a relatively low number of trainable parameters (1,639,582). This result indicates that MobileNet V2 offers a favorable balance between classification performance and computational efficiency. Other architectures, such as MobileNet V1 and VGG16, also achieved strong classification results; however, they involved trade-offs between model size and computational complexity. In contrast, deeper architectures such as ResNet exhibited higher parameter counts without yielding superior detection performance in this experimental setting.

To further examine the classification behavior of the selected model, a confusion matrix for MobileNet V2 is presented in Figure 6. The matrix illustrates the model's ability to accurately distinguish earthquake events from noise, with only a few misclassifications. This result suggests that MobileNet V2 effectively captures discriminative time–frequency patterns in seismic spectrograms, despite its lightweight architecture.

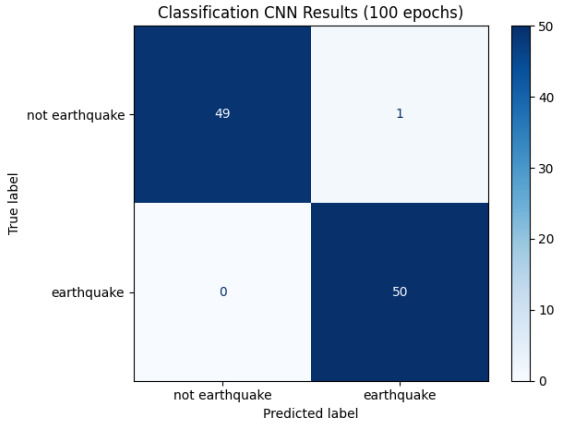


Fig. 6 Confusion Matrix Scenario 5 (MobileNet V2)

3.2 Model Loss and Accuracy Analysis

In addition to classification metrics, the learning behavior of the MobileNet V2 model was examined through training and validation accuracy and loss curves over 100 epochs. As illustrated in Figure 7, training accuracy increased rapidly during the initial epochs and gradually converged toward near-perfect performance. Validation accuracy followed a similar trend, stabilizing after approximately 30 epochs at around 93–94%. The observed gap between training and validation accuracy suggests that while the model learned highly discriminative features from the training data, a moderate generalization gap remains.

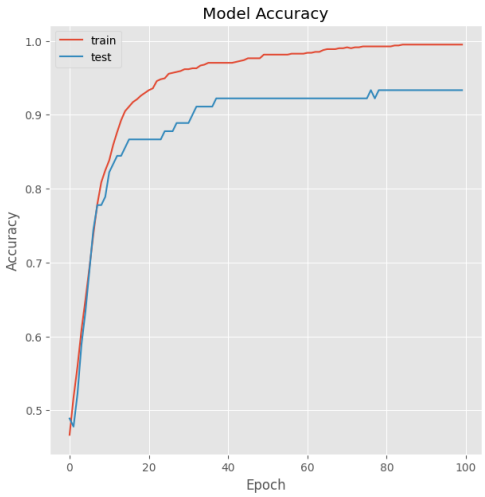


Fig. 7 Accuracy Curve MobileNetV2

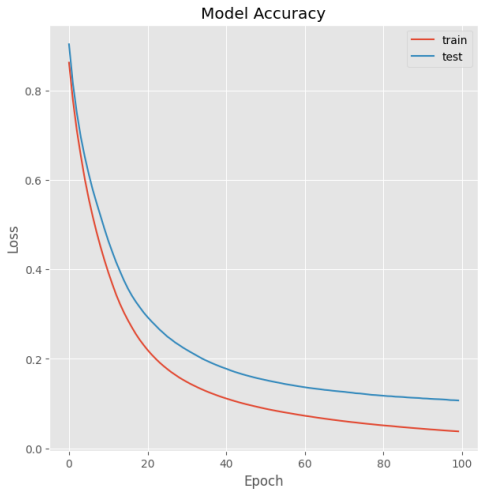


Fig. 8 Loss Curve MobileNet V2

Figure 8 shows the corresponding loss curves for training and validation phases. Both curves demonstrate a consistent downward trend, indicating effective optimization and convergence. Although the training loss decreases more rapidly than the validation loss, the validation loss continues to decline steadily without sudden divergence, suggesting that the model does not suffer from severe overfitting.

The consistency between the loss trends and the high classification performance observed in the confusion matrix (Figure 6) indicates that MobileNet V2 is capable of learning meaningful time–frequency representations from seismic spectrograms. Nevertheless, further validation using cross-station data splits or repeated experiments with different random seeds would provide a more comprehensive assessment of model robustness.

3.3 Discussion

The experimental results indicate that MobileNetV2 provides competitive performance compared to other convolutional neural network (CNN) architectures for binary earthquake detection using seismic spectrograms. While several models achieved high classification accuracy, MobileNetV2 demonstrated a favorable balance between detection performance and computational efficiency, as reflected by its relatively small number of trainable parameters and strong evaluation metrics. These characteristics make MobileNetV2 a promising candidate for deployment in resource-constrained environments, rather than conclusively superior to all alternative architectures.

The conversion of raw seismic waveform data into spectrogram representations was crucial for effective feature learning. By transforming one-dimensional time-series signals into two-dimensional time–frequency representations, the model could exploit the spatial feature-extraction capabilities inherent to CNN architectures. This representation is particularly advantageous for seismic signals, where important event characteristics may be distributed across both the time and frequency domains and are not easily captured from raw waveforms alone.

Using transfer learning with ImageNet-pretrained weights led to faster convergence and more stable training, despite the domain gap between natural images and seismic spectrograms. Leveraging pretrained visual features reduced the dependence on large volumes of labeled seismic data, which are often expensive and challenging to curate in geophysical applications. This finding aligns with prior studies demonstrating the effectiveness of transfer learning for spectrogram-based signal classification.

Although the obtained results are encouraging, several limitations should be acknowledged. The evaluation was conducted using a random data split without enforcing station-wise or region-wise separation, and the reported metrics were obtained from a single training configuration. Consequently, the results primarily reflect within-distribution performance. Further investigations involving cross-station validation, multiple training runs, and robustness analysis under varying noise conditions would provide a more comprehensive assessment of the model’s generalization capability.

Overall, this study demonstrates that lightweight CNN architectures such as MobileNetV2 can effectively support earthquake detection tasks while maintaining computational efficiency. Rather than introducing a new detection methodology, this work's contribution lies in empirically evaluating the suitability of MobileNetV2 for spectrogram-based seismic classification and highlighting its potential applicability in scalable, low-cost earthquake monitoring systems.

4. CONCLUSION

This study evaluated the effectiveness of a lightweight convolutional neural network, MobileNetV2, combined with transfer learning for binary earthquake detection using spectrogram representations of seismic waveform data. By transforming time-series signals into time–frequency images and applying a compact CNN architecture, the proposed approach achieved strong classification performance while maintaining relatively low computational complexity. When compared with several commonly used CNN architectures under the same experimental conditions, MobileNetV2 demonstrated a favorable balance between detection accuracy and model efficiency. These results indicate that lightweight deep learning models can serve as practical alternatives for earthquake detection tasks, particularly in scenarios with limited computational resources.

Although this study does not introduce a novel detection framework, it provides an empirical assessment of MobileNetV2’s suitability for spectrogram-based seismic classification. The findings suggest that such lightweight architecture holds potential for future deployment in mobile or embedded systems; however, real-time implementation and on-device performance evaluation were not addressed in the present work. Future research will focus on extending the evaluation using station- or region-wise data splits, conducting repeated experiments to assess robustness, and validating on real hardware platforms. In addition, incorporating multimodal seismic features and exploring alternative time–frequency representations may further enhance detection reliability. Overall, this work contributes to ongoing efforts toward scalable, computationally efficient

earthquake-monitoring solutions that support disaster preparedness in resource-constrained environments.

ACKNOWLEDGEMENTS
This work was supported by Nusa Mandiri University and Gazi University, which provided essential resources and assistance.

REFERENCES
[1] T. Perol, M. Gharbi, and M. Denolle, "Convolutional neural network for earthquake detection and location," *Sci. Adv.*, vol. 4, no. 2, Feb. 2018, doi: 10.1126/sciadv.1700578.
[2] Z. E. Ross, M. Meier, E. Hauksson, and T. H. Heaton, "Generalized Seismic Phase Detection with Deep Learning," *Bull. Seismol. Soc. Am.*, vol. 108, no. 5A, pp. 2894–2901, Oct. 2018, doi: 10.1785/0120180080.
[3] D. Zhexebay *et al.*, "Deep Learning for Early Earthquake Detection: Application of Convolutional Neural Networks for P-Wave Detection," *Appl. Sci.*, vol. 15, no. 7, p. 3864, Apr. 2025, doi: 10.3390/app15073864.
[4] S. M. Mousavi, Y. Sheng, W. Zhu, and G. C. Beroza, "STanford EArthquake Dataset (STEAD): A Global Data Set of Seismic Signals for AI," *IEEE Access*, vol. 7, pp. 179464–179476, 2019, doi: 10.1109/ACCESS.2019.2947848.
[5] S. M. Mousavi and G. C. Beroza, "Deep-learning seismology," *Science (80-.).*, vol. 377, no. 6607, Aug. 2022, doi: 10.1126/science.abm4470.
[6] Z. E. Ross, M. Meier, and E. Hauksson, "P Wave Arrival Picking and First-Motion Polarity Determination With Deep Learning," *J. Geophys. Res. Solid Earth*, vol. 123, no. 6, pp. 5120–5129, Jun. 2018, doi: 10.1029/2017JB015251.
[7] S. M. Mousavi, W. Zhu, Y. Sheng, and G. C. Beroza, "CRED: A Deep Residual Network of Convolutional and Recurrent Units for Earthquake Signal Detection," *Sci. Rep.*, vol. 9, no. 1, p. 10267, Jul. 2019, doi: 10.1038/s41598-019-45748-1.
[8] W. Zhu and G. C. Beroza, "PhaseNet: A Deep-Neural-Network-Based Seismic Arrival Time Picking Method," *Geophys. J. Int.*, Oct. 2018, doi: 10.1093/gji/ggy423.
[9] S. M. Mousavi, W. L. Ellsworth, W. Zhu, L. Y. Chuang, and G. C. Beroza, "Earthquake transformer—an attentive deep-learning model for simultaneous earthquake detection and phase picking," *Nat. Commun.*, vol. 11, no. 1, p. 3952, Aug. 2020, doi: 10.1038/s41467-020-17591-w.
[10] T. Lu *et al.*, "EQTypeNet: deep learning tri-branch earthquake automatic classification model and its application in China," *Geophys. J. Int.*, vol. 242, no. 3, Jul. 2025, doi: 10.1093/gji/ggaf263.
[11] A. Navarro-Rodríguez *et al.*, "Recent Advances in Early Earthquake Magnitude Estimation by Using Machine Learning Algorithms: A Systematic Review," *Appl. Sci.*, vol. 15, no. 7, p. 3492, Mar. 2025, doi: 10.3390/app15073492.
[12] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, IEEE, Jun. 2018, pp. 4510–4520. doi: 10.1109/CVPR.2018.00474.
[13] T. M. Pham *et al.*, "A CNN-LSTM Framework for Time-Windowed Detection of Local Earthquakes from Ocean Bottom Seismometer Data," *J. Robot. Control*, vol. 6, no. 6, p. 2025, 2025, doi: 10.18196/jrc.v6i6.28381.
[14] D. Başar and R. N. Çelik, "A Hybrid CNN-LSTM Architecture for Seismic Event Detection Using High-Rate GNSS Velocity Time Series," *Sensors*, vol. 26, no. 2, p. 519, Jan. 2026, doi: 10.3390/s26020519.
[15] I. Kaftan, "Machine Learning Applications for Earthquake Magnitude Prediction in Western Turkey," *Appl. Sci.*, vol. 15, no. 20, p. 10909, Oct. 2025, doi: 10.3390/app152010909.
[16] P. Welch, "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," *IEEE Trans. Audio Electroacoust.*, vol. 15, no. 2, pp. 70–73, Jun. 1967, doi: 10.1109/TAU.1967.1161901.
[17] Y. Shi, H. Tang, M. J. Baine, M. A. Hollingsworth, H. Du, and ..., "… Adversarial

Networks with a 3D U-Net Based Generator to Achieve the Accurate and Effective Synthesis of Clinical Tumor Image Data for Pancreatic Cancer," *Cancers (Basel).*, 2023, [Online]. Available: https://www.mdpi.com/2072-6694/15/23/5496

[18] B. A. Omodunbi *et al.*, "Stacked Ensemble Learning for Classification of Parkinson's Disease Using Telemonitoring Vocal Features," *Diagnostics*, vol. 15, no. 12, p. 1467, Jun. 2025, doi: 10.3390/diagnostics15121467.

[19] E. Patimah, V. B. Haekal, and D. Sandya Prasvita, "Klasifikasi Penyakit Liver dengan Menggunakan Metode Decision Tree," *Semin. Nas. Mhs. Ilmu Komput. dan Apl. Jakarta-Indonesia*, vol. 2, no. 1, pp. 655–659, 2021.

[20] M. R. Canal, "Comparison of Wavelet and Short Time Fourier Transform Methods in the Analysis of EMG Signals," *J. Med. Syst.*, vol. 34, no. 1, pp. 91–94, Feb. 2010, doi: 10.1007/s10916-008-9219-8.

[21] D. Griffin and Jae Lim, "Signal estimation from modified short-time Fourier transform," *IEEE Trans. Acoust.*, vol. 32, no. 2, pp. 236–243, Apr. 1984, doi: 10.1109/TASSP.1984.1164317.

[22] P. Ewert, B. Wicher, and T. Pajchrowski, "Application of the STFT for Detection of the Rotor Unbalance of a Servo-Drive System with an Elastic Interconnection," *Electronics*, vol. 13, no. 2, p. 441, Jan. 2024, doi: 10.3390/electronics13020441.

[23] M. A. Latumahina, H. Santoso, I. Wasito, and H. Haryono, "Emotion Recognition System Using Autoencoder + CNN + Attention," vol. 10, no. 4, pp. 150–161, 2023, [Online]. Available: http://jurnal.mdp.ac.id

[24] D. Baby, S. J. Devaraj, J. Hemanth, and M. M. Anishin Raj, "Leukocyte classification based on feature selection using extra trees classifier: A transfer learning approach," *Turkish J. Electr. Eng. Comput. Sci.*, vol. 29, no. 8, pp. 2742–2757, 2021, doi: 10.3906/elk-2104-183.

[25] R. Balestriero, L. Bottou, and Y. LeCun, "The Effects of Regularization and Data Augmentation are Class Dependent," *Adv. Neural Inf. Process. Syst.*, vol. 35, 2022, [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2022/hash/f73c04538a5e1cad40ba5586b4b517d3-Abstract-Conference.html

[26] M. Zakariah, S. A. AlQahtani, and M. S. Al-Rakhami, "Machine Learning-Based Adaptive Synthetic Sampling Technique for Intrusion Detection," *Appl. Sci.*, vol. 13, no. 11, p. 6504, May 2023, doi: 10.3390/app13116504.

[27] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

[28] G. W. Intyanto, "Klasifikasi Citra Bunga dengan Menggunakan Deep Learning: CNN (Convolution Neural Network)," *J. Arus Elektro Indones.*, vol. 7, no. 3, p. 80, Dec. 2021, doi: 10.19184/jaei.v7i3.28141.

[29] H. A. A. Rozaq, E. M. Özen, M. K. Altıparmak, and O. Yıldız, "A Hybrid Approach Combining Neural Networks and Signal Processing for Indoor Temperature Detection Using Plants' Bioelectric Potential," in *2025 9th International Symposium on Innovative Approaches in Smart Technologies (ISAS)*, IEEE, Jun. 2025, pp. 1–8. doi: 10.1109/ISAS66241.2025.11101899.

[30] I. M. Putra, I. Tahyudin, H. A. A. Rozaq, A. Y. Syafa'At, R. Wahyudi, and E. Winarto, "Classification analysis of COVID19 patient data at government hospital of banyumas using machine learning," in *2021 2nd International Conference on Smart Computing and Electronic Enterprise: Ubiquitous, Adaptive, and Sustainable Computing Solutions for New Normal, ICSCEE 2021*, Malaysia: IEEE, Jun. 2021, pp. 271–274. doi: 10.1109/ICSCEE50312.2021.9498020.