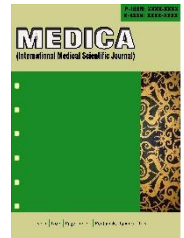
MEDICA

(International Medical Scientific Journal)
Vol.8, No.5, May 2026, pp. 345 – 357
ISSN 2622-660X (Online), ISSN 2622-6596 (Print)
https://journal.ahmareduc.or.id/index.php/medica



Development of A Website-Integrated MobileNet Model for Ischemic Stroke Detection Based on CT Scan Images

Naufal Lutfi Ardiawan[1]✉, Gatot Murti Wibowo[1], Sri Mulyati[1], Donny Kristanto Mulyantoro[1], Rasyid[1]

[1] Postgraduate Program Master in Applied Diagnostic Imaging, Politeknik Kesehatan Kementerian Kesehatan Semarang, Semarang City, Central Java, Indonesia

Info Article

Article History:
Received:
18 April 2026
Accepted:
31 May 2026
Published:
31 May 2026

Keywords:
Ischemic Stroke
MobileNet
Website
CT scan

Abstract

The prevalence of ischemic stroke in Indonesia continues to increase, highlighting the need for rapid and accurate diagnostic approaches. Computed Tomography (CT) imaging plays a crucial role in the early detection of ischemic stroke, particularly within the therapeutic window of 3–4.5 hours after symptom onset. This study aimed to develop and evaluate a website-based ischemic stroke detection system using a MobileNet deep learning model integrated with CT scan image analysis. A Research and Development (R&D) approach employing the Rapid Application Development (RAD) framework was applied. The model was developed using 2,000 CT scan images obtained from a Kaggle dataset, comprising 1,000 ischemic stroke images and 1,000 normal control images. The dataset was divided into training and validation sets, with 800 images per class used for training and 200 images per class used for validation. External clinical validation was conducted using 600 CT scan images collected from hospitals, consisting of 300 ischemic stroke images and 300 normal control images. Model performance was evaluated using accuracy, precision, sensitivity, and specificity metrics, while system usability was assessed using the System Usability Scale (SUS). The developed model achieved an accuracy of 92.25%, precision of 92.00%, sensitivity of 92.50%, and specificity of 92.00% on the validation dataset. However, performance decreased during external clinical testing, yielding an accuracy of 71.50%, precision of 73.12%, sensitivity of 68.00%, and specificity of 75.00%. These findings are consistent with previous studies indicating that models trained solely on public datasets often experience performance degradation when applied to real-world clinical data, emphasizing the importance of multi-institutional training datasets and extensive external validation. The usability evaluation produced an average SUS score of 83, indicating excellent user acceptance and system usability. The proposed website-based MobileNet model demonstrates strong potential as an accessible tool for supporting early ischemic stroke detection from CT scan images and may be further enhanced through the incorporation of multi-slice or volumetric imaging data to improve clinical performance.

Corresponding Author:
✉ Naufal Lutfi Ardiawan
Postgraduate Program Master in Applied Diagnostic Imaging, Politeknik Kesehatan Kementerian Kesehatan Semarang, Semarang City, Central Java, Indonesia
Email: naufallutfi2499@gmail.com

1. INTRODUCTION

Ischemic stroke is a condition where blood flow to the brain stops due to a blockage in the cerebral blood vessels (Dewi & Fitraneti, 2024). The blockage is caused by a blood clot, or thrombosis, that forms within a blood vessel or by a blood clot traveling from elsewhere in the body to the brain (embolism). When blood flow is interrupted, the brain's oxygen and nutrient supply is reduced, causing the death of brain cells in the affected area. This blockage can cause acute neurological disorders, such as hemiparesis, difficulty speaking (aphasia), and vision and cognitive impairment that can be long-lasting or permanent (Kovács et al., 2023; Pu et al., 2023).

Ischemic stroke accounts for approximately 80-85% of all stroke cases worldwide. Global Burden of Disease Study. In 2019, ischemic stroke resulted in more than 7.63 million new cases annually and was the leading cause of death. Stroke is the leading cause of long-term disability and the second leading cause of death worldwide (Feigin et al., 2021; Zhu et al., 2022). Riskesdas data shows that the prevalence of stroke increased from 7 per 1000 population in 2013 to 10.9 per 1000 population in 2018. This reflects the high burden of ischemic stroke in developing countries such as Indonesia (Herpich & Rincon, 2020). In the elderly population, the prevalence of ischemic stroke is increasing, with most cases occurring in individuals over the age of 60. Therefore, early detection and management of risk factors in elderly individuals is important to reduce the prevalence of ischemic stroke and its impact on quality of life (Hartanto, 2024; Wahyuningsih & Martiwi, 2025).

CT scan plays a crucial role in the early diagnosis of ischemic stroke, especially in the acute phase, where rapid imaging is essential to exclude bleeding and determine appropriate therapy. Non-contrast CT (NCCT) is a commonly used imaging modality in the initial evaluation of ischemic stroke. One of the key findings observed on CT during an ischemic event is early hypodensity, reflecting areas of reduced blood perfusion and cellular damage resulting from infarction. These hypodensity changes are important in differentiating between ischemic and hemorrhagic strokes, where hemorrhagic strokes will show areas of hyper density indicating bleeding (Nukovic & et all, 2023). Golden time in the management of ischemic stroke, it refers to the critical period that occurs in the first 3-4.5 hours after symptoms appear, where rapid medical intervention can minimize brain tissue damage and increase the patient's chances of neurological recovery (Ishariani & Rachmania, 2021). In clinical practice, delays often occur in the diagnosis and treatment of stroke. One contributing factor is the time required to read and interpret CT scan images. Research shows that the average time to CT scan in non-hemorrhagic stroke patients at a hospital in Semarang was 463.59 minutes, which is much longer than the time needed for optimal medical decision-making Click or tap here to enter text. The mean time for CT Scan examination from the onset of symptoms to neuroimaging examination in ischemic stroke patiens in Ghana was 28.2 hours. Click or tap here to enter text.To overcome these challenges, it is important to implement technology-based systems, such as artificial intelligence (AI), which can speed up CT scan interpretation automatically and increase efficiency in medical decision making, in accordance with the principles time is brain, which emphasizes the importance of rapid treatment in ischemic stroke patients.

Convolutional Neural Networks (CNN) has proven to be one of the main solutions in diagnosing ischemic stroke, thanks to its ability to automatically process and analyze medical images (Chen et al., 2022; Pan et al., 2021). CNNs offer exceptional accuracy, but the processing time required to analyze medical images poses a major challenge in emergency situations, especially when a diagnosis must be made within a limited timeframe. Research on the development of CNN with DenseNet201 in the detection of osteoarthritis obtained an average accuracy, sensitivity and specificity value of 87.6% and can be used as an alternative diagnostic tool while still referring to confirmation and justification by radiologists (Nurfadhillah et al., 2023). The development of more efficient and faster CNN models, such as MobileNet become important. MobileNet is a CNN architecture specifically designed to address the computational complexity issues of larger CNN models. Research shows MobileNet can maintain high accuracy in detecting lesions, while reducing the latency that often occurs in other CNN architectures, such as ResNet and Inception V3 (Alshardan et al., 2024). Research on CNN U-Net architecture can effectively perform segmentation automatic region of interest (ROI) of the kidney on renal scintigraphy images with high accuracy (Gitawiarsa et al., 2026).

Previous research shows the model MobileNet has excellent performance in medical image classification tasks, with high accuracy and minimal computational resource usage (Ogundokun, 2023). In addition, other studies confirm MobileNet offers an excellent balance between efficiency and accuracy, making it an ideal choice for disease detection, on systems with hardware limitations (Alshardan et al., 2024). Integration MobileNet the ischemic stroke detection system is expected to overcome the challenges of slow processing times, improve the speed of diagnosis, and support faster medical decision-making, which is crucial in the management of ischemic stroke patients. Previous research has shown that although CNNs can provide high accuracy, the time-consuming process limits their effectiveness in emergency situations, where rapid treatment is essential (Salehi et al., 2023). A limitation of previous CNNs is their relatively long processing time, so website-flask-based innovation is needed that offers real-time advantages. The novelty of this research is the development of a website-based CNN with Flask, thus enabling the trained CNN model to be accessed directly via a web-based platform. Implementation of Flask in a system based on a web for real-time processing. It is hoped that it will accelerate diagnosis and support more timely medical decision-making, which is very important in the management of ischemic stroke patients.The aim of this study is to develop a CT scan image-based ischemic stroke detection model by using MobileNet, which is integrated in website to speed up and simplify the process of diagnosing ischemic stroke.

2. METHOD

This study employed a Research and Development (R&D) approach using the Rapid Application Development (RAD) framework to develop and evaluate a website-based ischemic stroke detection system utilizing the MobileNet deep learning architecture. The study used a publicly available brain CT scan dataset obtained from Kaggle, consisting of axial non-contrast CT images, which represent the standard imaging modality for routine brain CT examinations and the primary diagnostic tool for acute ischemic stroke assessment.

The dataset comprised 2,000 CT scan images, including 1,000 normal control images and 1,000 ischemic stroke images. The images were divided into training and validation datasets, with 800 normal and 800 ischemic stroke images allocated for model training, while 200 normal and 200 ischemic stroke images were reserved for validation. To evaluate the model's generalizability in real-world settings, external clinical validation was performed using 600 CT scan images collected from Boyolali Regional Hospital, consisting of 300 normal control images and 300 ischemic stroke images.

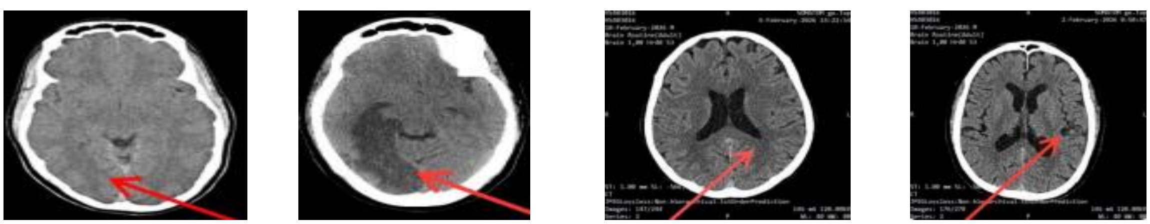
The inclusion criteria were high-resolution CT scan images with clear diagnostic labels and without significant image artifacts. The exclusion criteria included images with unclear labels, motion artifacts, image acquisition errors, or poor image quality that could affect interpretation and model performance.

The development process consisted of eleven stages. First, CT scan image datasets were collected and organized. Second, the required libraries for image preprocessing, model development, training, and evaluation were imported. Third, image classes were defined as either normal or ischemic stroke. Fourth, image preprocessing was conducted, including image normalization to standardize pixel intensity values, resizing all images to 512 × 512 pixels, and image augmentation to increase dataset variability and reduce the risk of overfitting. Fifth, the dataset was partitioned into training (80%) and validation (20%) subsets. Sixth, the MobileNet convolutional neural network architecture was implemented for image classification. Seventh, the model was trained using the prepared dataset. Eighth, model performance was evaluated using accuracy, precision, sensitivity, and specificity metrics. Ninth, external clinical validation was conducted using hospital-based CT scan images. Tenth, the web-based application framework was developed and integrated with the trained MobileNet model. Finally, website usability was assessed.

Descriptive quantitative analysis was used to summarize model performance and usability evaluation results. Website usability was evaluated using the System Usability Scale (SUS) questionnaire administered to five expert users, comprising two radiologists and three radiographers. SUS scores were analyzed descriptively to determine user acceptance and system usability. Ethical approval for the study was obtained from the Health Research Ethics Committee of Poltekkes Kemenkes Semarang (Approval No. 197/EA/F.XXIII.38/2026).

3. RESULTS AND DISCUSSION

The study used a public dataset of brain CT scans from Kaggle, and the images used were axial sections, as they are the gold standard for routine brain CT scans. The following is an overview of the dataset and clinical data for normal and ischemic CT scan images.



(a) (b) (c) (d)

Figure 1. (a) Dataset Image *Kaggle* Normal (b) Dataset Image *Kaggle* Stroke Ischemic; (c) Clinical image Normal (d) Clinical image Ischemic Stroke

In figures 1, CT scan images are shown *brain* between normal patients (a) and ischemic stroke (b) are image from the dataset *Kaggle*, while (c) and (d) are image of clinical data. In Figure (d) there is an arrow indicating the presence of hypodensity in the area *white matter*, which is one indication of the condition *ischemic stroke*.

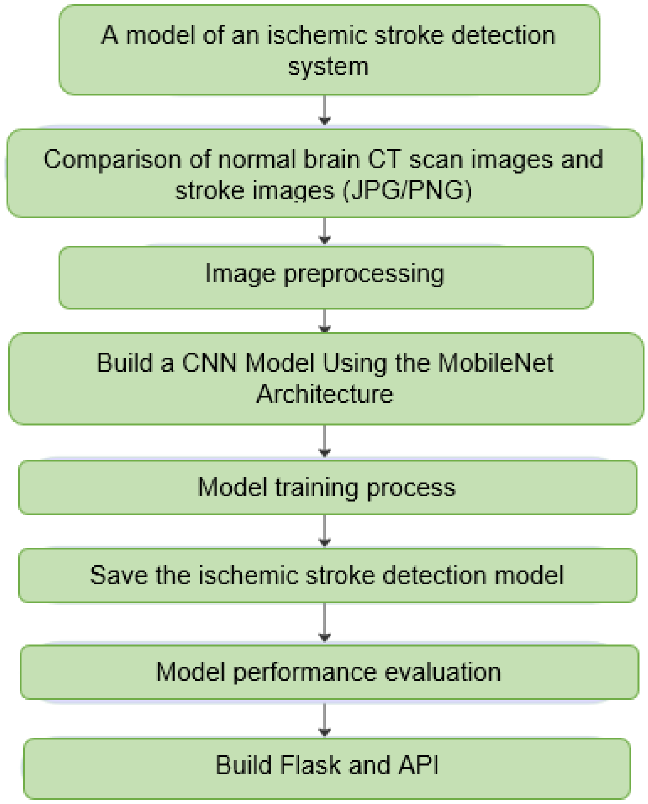


Figure 2. Flowchart detection model ischemic stroke CT scan image-based scan by using MobileNet.

The model training process is carried out with the MobileNetV2 architecture using training data and evaluating its performance on validation data for 75 epochs with a batch size of 16. The model will be saved if *val accuracy* increased. *Val loss* describes the size of the model prediction error on validation data. *Val loss* the decrease indicates that the error is getting smaller so that the generalization improves. Meanwhile, *val accuracy* shows the percentage of correct predictions on validation data, *val accuracy* increasing means the classification ability is getting better. The training process is shown in figure 4:

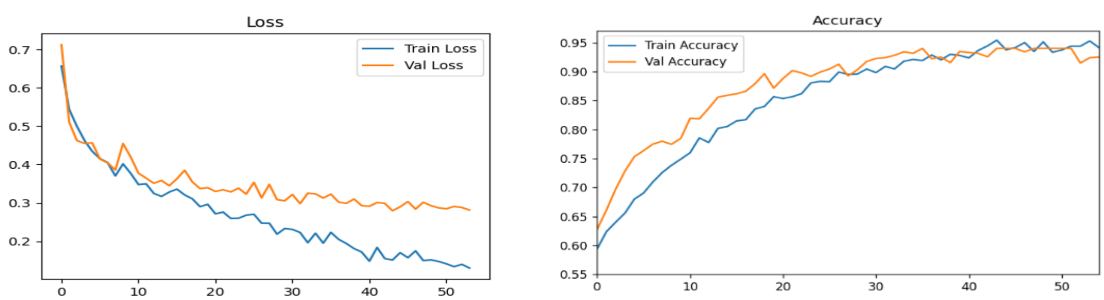


Figure 3. Graphics selection loss and val accuracy.

In Figure 3, the graph shows that the val loss is decreasing and the val accuracy is increasing, indicating that the learning process is running quite stably. Model evaluation using a *confusion matrix,* the validation data of 200 normal images and 200 ischemic images is shown in Figure 4 below:

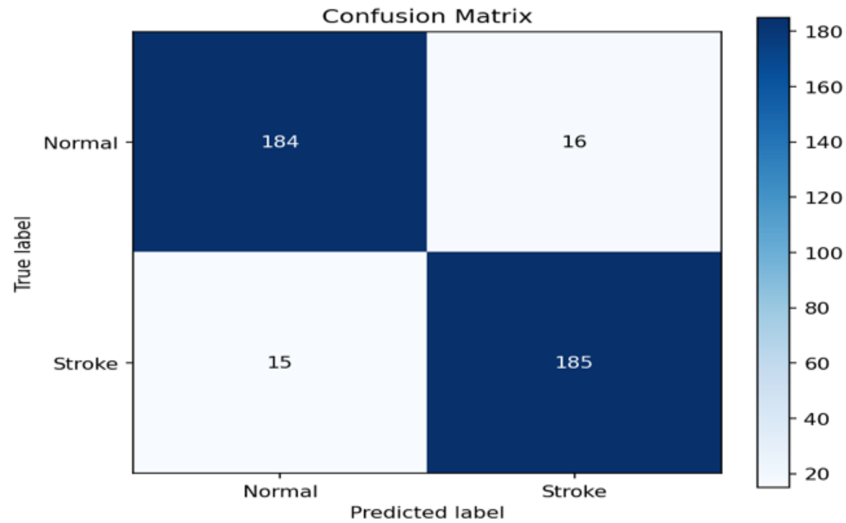


Figure 4. Confusion matrix for training data testing.

Figure 4 shows *confusion matrix* on a model trained to detect CT scan images normal and ischemic stroke. Based on *confusion matrix* the value is known TP is 185, which indicates the number of stroke cases that were correctly predicted as strokes. FN of 15, meaning the model still failed to detect 15 stroke cases and misclassified them as normal. Next, a more in-depth evaluation was conducted using accuracy, precision, sensitivity, and specificity metrics to comprehensively describe the model's performance.

Table 1. Evaluation matrix of data set model of detection system for ischemic stroke.

Metrics	**Yield (%)**
Accuracy	92.25%
Precision	92.00%
Sensitivity	92.50%
Spesifisity	92.00%

Based on Table 1, it shows good model performance and is relatively balanced in both groups.

Model evaluation on clinical datasets was performed using CT scan images *brain* non-contrast cuts *axial* at Boyolali Regional Hospital. The evaluation stage was carried out using *confusion matrix*. Here are the results *confusion matrix* from model testing on the clinical dataset used:

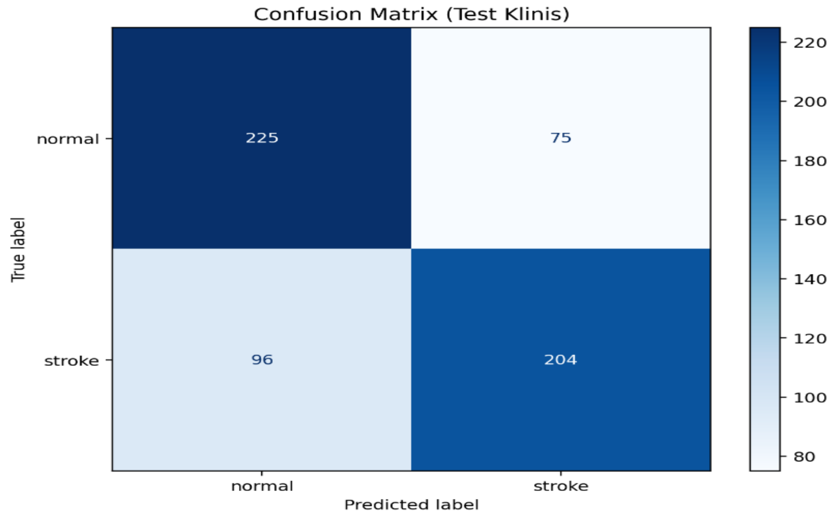


Figure 5. Confusion matrix of clinical data testing

Figure 5. shows *confusion matrix* for models trained to detect CT scan images normal and ischemic stroke in clinical data. A TP value of 204 indicates the number of stroke cases correctly predicted as stroke. A FN of 96 means the model still failed to detect 96 stroke cases and incorrectly classified them as normal. Furthermore, based on*confusion matrix* more detailed performance metrics were calculated, namely accuracy, precision, sensitivity, and specificity.

Table 2. Evaluation of Clinical Data Model Performance.

Metrics	**Yield (%)**
Accuracy	71.50%
Precisio	73.12%
Sensitivity	68.00%
Spesifisity	75.00%

The evaluation results using clinical data showed that the model performance decreased compared to the results on the validation data.

The SUS questionnaire was administered to radiographers and radiologists as users directly involved in CT scan examinations and image interpretation. Respondents were asked to try the main flow *website*, including *login*, filling in patient data, uploading CT images, viewing detection results, and downloading results. The obtained SUS score is used to quantitatively describe the quality of the user experience and assess whether *website* has been quite easy to operate as a medium for implementing an ischemic stroke detection model.

Rating *usability website* this study involved 5 respondents consisting of 3 radiographers and 2 radiologists. The characteristics of the respondents were 4 (80%) men and 1 (20%) woman. The age of the respondents was 25-39 years old (2 people) (40%) and 40-54 years old is 3 people (60%). The SUS score results of each respondent were in the range of 80-85 with an average of 83, which indicates a good assessment *usability website* relatively consistent and high among respondents.

The performance of a model is greatly influenced by the quality and quantity of the dataset (Schmidt et al., 2024). Research on the optimal kernel in the thorax lung window CT scan to produce optimal anatomical image quality is the U90 kernel (Bequet et al., 2019). This research uses a dataset *open-source* obtained from *Kaggle*. *Kaggle* is one of the *platform crowdsourcing* which is often used in data *science* and provide a variety of *real-life* data *science challenges* and has been widely used by many researchers (Li et al., 2024). In addition, the dataset *open source* also supports transparency and reproducibility and encourages datasets to become more *accessible, inclusive*, and representative (Alberto et al., 2023). The larger the size of a dataset, the longer the model training time will be (Zantvoort et al., 2024).This dataset was balanced to reduce the risk of model bias in predicting the majority class. Previous research has shown that an unbalanced dataset will bias the model toward the majority class, resulting in lower detection performance for the minority class (Gentili et al., 2024). In addition, a balanced dataset can also maintain more stable performance (Gurcan & Soylu, 2024).

Level I*mport library* is the process of calling and including a library (*library*/module) into the program so that the functions, classes, and methods contained within it can be used. Next, the process is carried out *define class* which functions to define the class groups that exist in the model as well as the related data and functions that are neatly arranged, can be reused, and are easy to develop (Gleixner et al., 2021). Next stage *image preprocessing* is the initial stage of preparing raw images before they are analyzed or modeled, with the aim of improving the quality and uniformity of the image, so that the algorithm can learn patterns more effectively and produce more accurate performance (Archana & Jeevaraj, 2024). *Image preprocessing* used in this study is *resize* and *normalize.* Previous research stated that 512×512 resolution images from the MIT dataset *Indoors scenes* showed quite satisfactory results, namely an increase in Top-1 accuracy of 3% to 26% (Rahimzadeh et al., 2024).

In this study, the dataset from *Kaggle.* It is divided into two groups training data and validation data. Training data is the data set used to train the model to learn patterns during the learning process. Validation data is a separate data set used during training to periodically evaluate the model's performance (Liu et al., 2025). Research by Bichri et al. (2024) shows that using a training data proportion of more than 70% tends to provide more optimal model performance (Bichri et al., 2024). After the dataset is divided, the model development stage continues. The ischemic stroke detection model in this study uses a CNN architecture *MobileNet*. This architecture was chosen because *MobileNet* is a lightweight CNN architecture from *Google* which prioritizes computational efficiency for image classification/detection tasks on limited devices by utilizing *depth wise separable convolution* so that the number of parameters and computational load are reduced significantly without a large decrease in accuracy (Howard et al., 2017). Research on the development of a data recording system using the Rapid Application Development method, integrated with HMSI on web-based CT-Scan examinations at Bhayangkara Level I Hospital showed very good results (Hayati et al., 2024).

The next stage is the model training process which is carried out for 75 *epoch* with *batch size* 16, so that the weight updates are carried out gradually and stably at each iteration *mini-batch.* Election 75 *epoch* aims to provide sufficient time for the model to learn image patterns optimally (Miseta et al., 2024). To maintain model quality and prevent *overfitting*, used *Early Stopping* which will stop training when performance on validation data no longer improves over a number of times *epoch* certain (Miseta et al., 2024). In addition, the Model *Checkpoint* applied to save the best performing models based on validation metrics *Val Accuracy,* so that the final model used is the model in the most optimal condition during training. Training is also supported by *Learning Rate Schedule,* namely the learning rate setting that is adjusted throughout the training process so that optimization is more effective (Albarrak et al., 2022).

The training data accuracy score of 92.25% indicates that the model has high classification accuracy, which is important in a medical context because it directly impacts patient safety and the accuracy of clinical decisions. Higher diagnostic accuracy supports improved service quality through earlier detection and reduced errors, as well as strengthening patient trust in the communication and management process (Alharbi et al., 2025). A precision value of 92.00% indicates that most of the positive predictions generated by the model are true positive cases, so the risk *false positive* and the potential for unnecessary management can be reduced. Precision plays a crucial role in medical diagnosis because it reflects the system's accuracy in identifying disease, especially in conditions with overlapping symptoms, thus making clinical decisions more targeted (Hussain et al., 2022). The sensitivity value of 92.50% shows that the model has a high ability to identify true positive stroke cases, so that the risk of stroke occurring is reduced *false negative* or undetected cases can be suppressed. High sensitivity plays a crucial role in supporting early detection and minimizing delays in treatment that could potentially worsen outcomes.

The specificity value of 92.00% indicates that the model is able to correctly recognize normal cases in a large proportion, so that the possibility of *false positive* and unnecessary interventions can be minimized. Detection model research *parkinson disease* based on *deep learning* using VGG Architecture has very high capability in classifying *parkinson disease* MRI images-based and consistently recognizes subtle neurodegenerative patterns in the substantia nigra, so this model has potential as an early screening tool (Lestari et al., 2026)

Based on the evaluation results on clinical datasets, model performance decreased compared to results on public data. Compared to previous performance (±92% accuracy), there was a decrease of approximately 20% in accuracy, indicating limited model generalizability when applied to real-world data. The most significant decrease was seen in sensitivity (68.00%), indicating an increased risk of undetected cases (*false negative*) in a clinical context. This is due to differences in data characteristics between the training dataset and the clinical trial dataset. Previous research has shown that an ophthalmology AI model trained on six public datasets experienced a decrease in AUC from approximately 95% to 76.6% when tested on real clinical data. Furthermore, a multi-hospital study in the ICU showed that the model *deep learning* that performed very well in their home hospital experienced a reduction in AUROC of up to 0.20 when applied to other institutions (Rockenschaub et al., 2024). Other studies also show a decrease in the performance of sepsis prediction models due to *temporal dataset shift* in electronic medical record data (Guo et al., 2022). In general, this performance decline is caused by variations in patient populations, differences in examination protocols and imaging devices, and more heterogeneous image quality.

In terms of system flow, the process starts when the user accesses *website* and do *login* to ensure authenticated access. In this study, *website* ischemic stroke detection (Sides-CT) obtained an average SUS score of 83 and was included in the category *acceptable* so that it quantitatively describes that users assess *website* relatively easy to understand, comfortable to operate, and supports the efficient completion of main tasks (Alshamari, 2016). *Benchmark* SUS score used in *website* in literature *digital health* mentions a score of 68 as a useful reference value for distinguishing *usability* “below” and “above” the average, therefore website it's quite good with the above average category (Hyzy et al., 2022). In addition, the SUS value category according to Van der Nat et al. (2022) states that SUS values with a range of 71.5–85.5 are included in the category *usability* "very good", while 85.6–100 is in the highest category (Van der Nat et al., 2022). SUS value on *website* Sides CT of 83 is in the range of 71.5–85.5, then website can be said to have quality *usability* “very good” based on that classification. Another study reported a mean SUS of 74.3 and found that very positive experiences correlated with increased perception suability, while very negative experiences correlated with a decrease usability (Simola et al., 2023). Existence website. This only complements, not replaces the role of clinicians and human elements in health services.

Although the results of this study are quite good, there are still several limitations that can be developed in further research. This study still uses a single slice as input, so spatial information between slices is not analyzed. This condition has the potential to cause problems. *Slice selection* Bias reduces the model's ability to capture ischemic lesion variations for more accurate interpretation. Performance decreases on clinical data, resulting in suboptimal generalization. While the model performed well on public data, clinical data testing showed lower performance, indicating generalization challenges when applied to real-world data.

4. CONCLUSION

Development of an ischemic stroke detection model based on CT scan images shows high usability. It is suggested that the development of stroke detection models is not limited to single-slice (2D), but extended to multi-slice or volumetric (3D) so that inter-slice anatomical information can be utilized and lesion representation becomes more comprehensive. In addition, it is necessary dataset expansion, particularly on multi-institutional clinical data that includes a variety of devices and examination protocols, as well as the implementation of generalization enhancement strategies to reduce performance degradation during real-world implementation. Website, development can be directed at strengthening implementation support features such as more informative reporting, activity recording (logging), and evaluation usability continued with mixed methods so that interface improvements and usage flows are more based on user needs wedges.

5. ACKNOWLEDGEMENT

We would like to thank Boyolali Regional Hospital for granting research permission.

REFERENCES

Albarrak, K., Gulzar, Y., Hamid, Y., Mehmood, A., & Soomro, A. B. (2022). A Deep Learning-Based Model for Date Fruit Classification. *Sustainability*, 14(10), 6339. https://doi.org/10.3390/su14106339

Alberto, I. R. I., Alberto, N. R. I., Ghosh, A. K., Jain, B., Jayakumar, S., Martinez-Martin, N., McCague, N., Moukheiber, D., Moukheiber, L., Moukheiber, M., Moukheiber, S., Yaghy, A., Zhang, A., & Celi, L. A. (2023). The impact of commercial health datasets on medical research and health-care algorithms. *The Lancet*, 5(5), e288–e294. https://doi.org/10.1016/S2589-7500(23)00025-0

Alharbi, T. A. F., Rababa, M., Alsuwayl, H., Alsubail, A., & Alenizi, W. S. (2025). Diagnostic Challenges and Patient Safety: The Critical Role of Accuracy - A Systematic Review. *Journal of multidisciplinary healthcare,* 18, 3051–3064. https://doi.org/10.2147/JMDH.S512254

Alshamari, M. (2016). Usability Factors Assessment in Health Information System. *Intelligent Information Management*, 8(6), 170–180. https://doi.org/10.4236/iim.2016.86012

Alshardan, A., Mahgoub, H., Alruwais, N., Darem, A. A., Almukadi, W. S., & Mohamed, A. (2024). Deep learning solutions for inverse problems in advanced biomedical image analysis on disease detection. *Scientific reports*, 14(1), 18478. https://doi.org/10.1038/s41598-024-69415-2

Archana, R., & Jeevaraj, P. S. E. (2024). Deep learning models for digital image processing: a review. *Artificial Intelligence Review*, 57,11. https://doi.org/10.1007/s10462-023-10631-z

Bequet, A. Y., Kartikasari, Y., Mulyati, S., Isnoviasih, S. T., Teknik, J., Dan, R., Poltekkes, R., & Semarang, K. (2019). Analisis Image Quality CT Scan Thorax Dengan Variasi Lung Window Kernel pada MSCT Siemens Somatom Emotion 6. *Jurnal Imejing Diagnostik (JImeD)*, 5, 55–59. http://ejournal.poltekkes-smg.ac.id/ojs/index.php/jimed/index

Bichri, H., Chergui, A., & Hain, M. (2024). Investigating the Impact of Train / Test Split Ratio on the Performance of Pre-Trained Models with Custom Datasets. In *IJACSA) International Journal of Advanced Computer Science and Applications,* 15(2), 331-339.

Chen, W., Wu, J., Wei, R., Wu, S., Xia, C., Wang, D., Liu, D., Zheng, L., Zou, T., Li, R., Qi, X., & Zhang, X. (2022). Improving the diagnosis of acute ischemic stroke on non-contrast CT using deep learning: a multicenter study. *Insights into imaging,* 13(1), 184. https://doi.org/10.1186/s13244-022-01331-3

Dewi, L., & Fitraneti, E. (2024). (2024). Stroke Iskemik. *Scientific Journal*, *3*(6), 379–388. https://doi.org/10.56260/sciena.v3i6.173

Feigin, V., Stark, B.A., Johnson, C.O., Roth, G.A., Bisignano, C., Abady, G.G., &…, Murray, C.J.L. (2021). Global, regional, and national burden of stroke and its risk factors, 1990-2019: A systematic analysis for the Global Burden of Disease Study 2019. *The Lancet Neurology*, 20(10), 1–26. https://doi.org/10.1016/S1474-4422(21)00252-0

Gentili, E., Franchini, G., Zese, R., Alberti, M., Ferrara, M., Domenicano, I., & Grassi, L. (2024). Machine learning from real data: A mental health registry case study. *Computer Methods and Programs in Biomedicine Update*, 5, 100132. https://doi.org/10.1016/j.cmpbup.2023.100132

Gitawiarsa, I. P. P. W., Guruh, B., Dartini, D., Mulyantoro, D. K., Masrochah, S., & Wibowo, G. M. (2026). Evaluasi Efektivitas Model U-Net untuk Segmentasi Citra Renal Scintigraphy pada Penilaian Fungsi Ginjal. *MAHESA : Malahayati Health Student Journal*, 6(4), 106–119. https://doi.org/10.33024/mahesa.v6i4.22074

Gleixner, A., Hendel, G., Gamrath, G., Achterberg, T., Bastubbe, M., Berthold, T., Christophel, P., Jarck, K., Koch, T., Linderoth, J., Lübbecke, M., Mittelmann, H. D., Ozyurt, D., Ralphs, T. K., Salvagnin, D., & Shinano, Y. (2021). MIPLIB 2017: data-driven compilation of the 6th mixed-integer programming library. *Mathematical Programming Computation*, 13(3), 443–490. https://doi.org/10.1007/s12532-020-00194-3

Guo, L. L., Pfohl, S. R., Fries, J., Johnson, A. E. W., Posada, J., Aftandilian, C., Shah, N., & Sung, L. (2022). Evaluation of domain generalization and adaptation on improving model robustness to temporal dataset shift in clinical medicine. *Scientific reports,* 12(1), 2726. https://doi.org/10.1038/s41598-022-06484-1

Gurcan, F., & Soylu, A. (2024). Learning from Imbalanced Data: Integration of Advanced Resampling Techniques and Machine Learning Models for Enhanced Cancer Diagnosis and Prognosis. *Cancers,* 16(19), 3417. https://doi.org/10.3390/cancers16193417

Hartanto, W. A. (2024). Correlation Between Blood Glucose Levels And Risk Of Non-Hemorrhagic Stroke_ Analysis of A Prospective Cohort Study In An Elderly Population. *Health Sains*, *5*(4), 284–292.

Hayati, N., Sudiyono, S., Handoko, B. D., Budiati, T. A., Kartikasari, Y., & Wibowo, G. M. (2024). Transforming CT-Scan Scheduling System in Hospital Through Web-Based Technology. *JMMR (Jurnal Medicoeticolegal Dan Manajemen Rumah Sakit)*, 13(3), 332–346. https://doi.org/10.18196/jmmr.v13i3.463

Herpich, F., & Rincon, F. (2020). Management of Acute Ischemic Stroke. *Critical care medicine, 48*(11), 1654–1663. https://doi.org/10.1097/CCM.0000000000004597

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. *Computer Vision and Pattern Recognition, 1-9*. http://arxiv.org/abs/1704.04861

Hussain, S., Mubeen, I., Ullah, N., Shah, S. S. U. D., Khan, B. A., Zahoor, M., Ullah, R., Khan, F. A., & Sultan, M. A. (2022). Modern Diagnostic Imaging Technique Applications and Risk Factors in the Medical Field: A Review. *BioMed research international*, 2022, 5164970. https://doi.org/10.1155/2022/5164970

Hyzy, M., Bond, R., Mulvenna, M., Bai, L., Dix, A., Leigh, S., & Hunt, S. (2022). System Usability Scale Benchmarking for Digital Health Apps: Meta-analysis. J*MIR mHealth and uHealth,* 10(8), e37290. https://doi.org/10.2196/37290

Ishariani, L., & Rachmania, D. (2021). Hubungan Respon Time Keluarga dalam Membawa Pasien Stroke ke Pelayanan Kesehatan dengan Tingkat Keparahan Pasien Stroke. *The Indonesian Journal of Health Science*, 13(1), 35–43. https://doi.org/10.32528/ijhs.v13i1.5274

Kovács, K. B., Bencs, V., Hudák, L., Oláh, L., & Csiba, L. (2023). Hemorrhagic Transformation of Ischemic Strokes. *International journal of molecular sciences,* 24(18), 14067. https://doi.org/10.3390/ijms241814067

Lestari, D., Wibowo, G.M., Setiawan, A.N., Suwondo, A., & Susanto, E. (2026). Model Deteksi Parkinson Disease Berbasis Deep Learning Menggunakan Arsitektur VGG. *Journal Imeging Diagnostik*, 12(1), 34–39. https://doi.org/10.31983/jimed.v12i1.14284

Li, L., Yu, H., & Kunc, M. (2024). The impact of forum content on data science open innovation performance: A system dynamics-based causal machine learning approach. *Technological Forecasting and Social Change*, 198, 1-22. https://doi.org/10.1016/j.techfore.2023.122936

Liu, Y., Xu, Y., Guo, L., Chen, Z., Xia, X., Chen, F., Tang, L., Jiang, H., & Xie, C. (2025). Development and external validation of machine learning models for the early prediction of malnutrition in critically ill patients: a prospective observational study. *BMC medical informatics and decision making,* 25(1), 248. https://doi.org/10.1186/s12911-025-03082-9

Miseta, T., Fodor, A., & Vathy-Fogarassy, Á. (2024). Surpassing early stopping: A novel correlation-based stopping criterion for neural networks. *Neurocomputing*, 567, 127028. https://doi.org/10.1016/j.neucom.2023.127028

Nukovic, J. J., Opancina, V., Ciceri, E., Muto, M., Zdravkovic, N., Altin, A., Altaysoy, P., Kastelic, R., Velazquez Mendivil, D. M., Nukovic, J. A., Markovic, N. V., Opancina, M., Prodanovic, T., Nukovic, M., Kostic, J., & Prodanovic, N. (2023). Neuroimaging Modalities Used for Ischemic Stroke Diagnosis and Monitoring. *Medicina (Kaunas, Lithuania),* 59(11), 1908. https://doi.org/10.3390/medicina59111908

Nurfadhillah, D., Santoso, G., Fatimah, Murti Wibowo, G., Darmini, & Nuryatno. (2023). Effectiveness of Automatic Detection of Osteoarthritis using Convolutional Neural Network (CNN) Method with DenseNet201 on Digital Images of Knee Joint Radiography. *E3S Web of Conferences*, 448, 1-10. https://doi.org/10.1051/e3sconf/202344802052

Ogundokun, R.O., Misra, S., Akinrotimi, A.O., Hasan Ogul, H. (2023). MobileNet-SVM: A Lightweight Deep Transfer Learning Model to Diagnose BCH Scans for IoMT-Based Imaging Sensors. *Sensors*, 23(2), 656. https://doi.org/10.3390/s23020656

Pan, Y., Zhang, H., Yang, J., Guo, J., Yang, Z., Wang, J., & Song, G. (2021). Identification and Diagnosis of Cerebral Stroke through Deep Convolutional Neural Network-Based Multimodal MRI Images. *Contrast media & molecular imaging,* 2021, 7598613. https://doi.org/10.1155/2021/7598613

Pu, L., Wang, L., Zhang, R., Zhao, T., Jiang, Y., & Han, L. (2023). Projected Global Trends in Ischemic Stroke Incidence, Deaths and Disability-Adjusted Life Years From 2020 to 2030. *Stroke*, 54(5), 1330–1339. https://doi.org/10.1161/STROKEAHA.122.040073

Rahimzadeh, M., Askari, A., Parvin, S., Safi, E., & Mohammadi, M. R. (2024). *Wise-SrNet: A Novel Architecture for Enhancing Image Classification by Learning Spatial Resolution of Feature Maps.* Berlin: Springer-Verlag. https://doi.org/10.1007/s10044-024-01211-0

Rockenschaub, P., Hilbert, A., Kossen, T., Elbers, P., Von Dincklage, F., Madai, V. I., & Frey, D. (2024). The Impact of Multi-Institution Datasets on the Generalizability of Machine Learning Prediction Models in the ICU. *Critical Care Medicine*, 52(11), 1710–1721. https://doi.org/10.1097/CCM.0000000000006359

Salehi, A. W., Khan, S., Gupta, G., Alabduallah, B. I., Almjally, A., Alsolai, H., Siddiqui, T., & Mellit, A. (2023). A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope. In *Sustainability (Switzerland)*, 15(7), 5930. https://doi.org/10.3390/su15075930

Schmidt, J., Cerqueira, T. F. T. ; Romero, A. H., Loew, A. , Jäger, F., Wang, H.-C., Botti, S., Marques, M. A. L. (2024). Improving machine-learning models in materials science through large datasets. *Materials Today Physics*, 48 (101560), 1-11. https://doi.org/10.3929/ethz-b-000698132

Simola, S., Hörhammer, I., Xu, Y., Bärkås, A., Fagerlund, A. J., Hagström, J., Holmroos, M., Hägglund, M., Johansen, M. A., Kane, B., Kharko, A., Scandurra, I., & Kujala, S. (2023). Patients' Experiences of a National Patient Portal and Its Usability: Cross-Sectional Survey Study. *Journal of medical Internet research,* 25, e45974. https://doi.org/10.2196/45974

Van der Nat, D. J., Huiskes, V. J. B., Taks, M., Pouls, B. P. H., van den Bemt, B. J. F., & van Onzenoort, H. A. W. (2022). Usability and perceived usefulness of patient-centered medication reconciliation using a personalized health record: a multicenter cross-sectional study. *BMC health services research,* 22(1), 776. https://doi.org/10.1186/s12913-022-07967-7

Wahyuningsih, E. P., & Martiwi, I. N. A. (2025). Diversity of Bryophytes Based on Substrate Types in the Karangkamulyan Tourist Area, Ciamis Regency. *Jurnal Biologi Tropis,* 25(1), 517-528. https://doi.org/10.29303/jbt.v25i1.8495

Zantvoort, K., Nacke, B., Görlich, D., Hornstein, S., Jacobi, C., & Funk, B. (2024). Estimation of minimal data sets sizes for machine learning predictions in digital mental health interventions. *NPJ digital medicine,* 7(1), 361. https://doi.org/10.1038/s41746-024-01360-w

Zhu, H., Hu, S., Li, Y., Sun, Y., Xiong, X., Hu, X., Chen, J., & Qiu, S. (2022). Interleukins and Ischemic Stroke. *Frontiers in immunology,* 13, 828447. https://doi.org/10.3389/fimmu.2022.828447