Journal of Intelligent Decision Support System (IDSS) 7 (2) (2024), pp. 121-129

Published by: Institute of Computer Science (IOCS)

Journal of Intelligent Decision Support System (IDSS)

Journal homepage: www.idss.iocspublisher.org

Application of artificial neural network method for early detection of dengue fever

Sarif Surorejo[1], Isna Lidia Ningrum[2], Pingky Septiana Ananda[3] , Gunawan Gunawan[4]

[1,2,3]Information System, STMIK YMI TEGAL, Tegal City, Indonesia
[4]Informatic Engineering, STMIK YMI TEGAL, Tegal City, Indonesia

Article Info

Article history:

Received Jun 01, 2024
Revised Jun 04, 2024
Accepted Jun 11, 2024

Keywords:

Artificial Neural Networks
Dengue Fever
Diagnostic Accuracy
Machine Learning Techniques
Medical Intervention

ABSTRACT

Dengue fever is a tropical disease whose diagnosis is often delayed due to limitations of conventional diagnostic methodologies, which have an impact on the effectiveness of medical interventions. This research is designed to develop an Artificial Neural Network (ANN) model aimed at improving accuracy and speed in dengue diagnosis. Through quantitative methods, clinical data from 50 patients during the period 2020-2021 were analyzed using machine learning techniques to train the ANN model, including the process of data normalization and selection of relevant features. The test results of the model showed excellent diagnostic performance with accuracy reaching 87%, precision 92%, and F1-Score 92%, indicating its effective ability to identify positive and negative cases. The conclusion of this study is that the developed ANN model is able to overcome the limitations of conventional diagnostics and shows significant potential in improving medical responses to dengue outbreaks. Further research is recommended to expand the datasets used in order to improve the validation and generalization of the model in the context of broader clinical applications.

Corresponding Author:

Isna Lidia Ningrum,
Information System,
STMIK YMI TEGAL,
1 Pendidikan Street, Tegal City, Central Java 52142, Indonesia
Email: isnalidia0803@gmail.com

Introduction

Dengue fever is an infectious disease caused by the dengue virus, and is found in tropical and subtropical regions (Wu et al., 2022)(Li et al., 2020). Dengue fever is often difficult to detect in the early stages because the symptoms are similar to other febrile diseases (Buonora et al., 2020)(Rathore et al., 2020). Due to delays in diagnosis and treatment, the risk of serious complications to death increases (Hanna et al., 2020)(Al-Ani et al., 2020). Therefore, Early detection of dengue fever is essential for outbreak control, improving treatment outcomes, and reducing the burden on health systems (Wong et al., 2022). Delayed diagnosis can increase the risk of morbidity and mortality because patients may experience serious complications that require intensive care (Cortés-Beringola et al., 2021).

The gap in existing research lies in the limitations of conventional diagnostic methods that often take a long time to produce results and are sometimes less sensitive. Lack of access to health facilities in some areas increases this challenge (Yang et al., 2020). The application of Artificial Neural Network (ANN) methods in this study is explored for faster, accurate, and accessible early detection, overcoming the shortcomings of traditional methods using advanced information technology(Kurucan et al., 2024)(Ansari et al., 2020). The ANN model is trained to recognize clinical patterns at an early stage, allowing for rapid medical response and wide deployment of the technology, even in areas with limited facilities. ANNs can improve the diagnosis process through data normalization and selection of relevant features, continuous training, and identification of complex patterns. This research helps reduce misdiagnosis and allows for more effective early detection.

This study aims to develop an optimized ANN model, which is able to classify the presence of dengue fever quickly and accurately based on early symptoms and other clinical parameters. The model is designed to facilitate healthcare workers in a more accurate and responsive diagnosis process, enabling timely medical intervention(Zhong et al., 2023)(Trenfield et al., 2022). Through interdisciplinary cooperation that integrates computer science and health, the use of these advanced technologies not only accelerates early detection, but also improves the effectiveness of disease control and management (Goes et al., 2021). This paves the way for further development in disease detection technologies, particularly in the face of global challenges such as dengue, providing new insights and concrete evidence regarding the effectiveness of ANN in the treatment of public health problems.

Previous research offers deep insights in various scientific fields. The object of this research is material constitutive modeling using Thermodynamics-based Artificial Neural Networks (TANNs) which integrate thermodynamic principles in neural network architecture resulting in more accurate and consistent predictions (Masi et al., 2021). Subsequent research focused on temporal trends and spatial clustering of dengue prevalence in West Java, Indonesia using the Richards model to identify the peak and distribution of dengue infections, supporting optimization of local intervention programs (Fauzi et al., 2022). Research conducted on the use of Neural Population Geometry to understand neural networks with population geometry analysis methods that provide new insights into the coding and processing of neural information (Chung & Abbott, 2021). Recent research on dengue outbreaks on Cook Island using disease surveillance methods and vector control resulted in an effective response in the face of a deathless outbreak (Uwishema et al., 2021).

Some researchers are focusing on integrating thermodynamic principles in ANN architecture, as observed in the use of Thermodynamics-based Artificial Neural Networks (TANNs) that produce more accurate and consistent predictions of disease dynamics. In addition, there are studies that focus on analyzing temporal trends and spatial clustering of dengue prevalence using the Richards model, which helps in the identification and distribution of infection on a local scale. However, there is limited research relating to the application of Neural Population Geometry methods in the context of public health to improve the process of coding and processing neural information in the diagnosis of infectious diseases such as dengue. Therefore, this study intends to develop and optimize an ANN model that can effectively classify the presence of dengue fever based on early symptoms and other clinical parameters quickly and accurately.

Method

Research Design

This research design uses a quantitative approach by combining experimental methods for data collection, quantitative analysis for data processing and analysis, and model validation to evaluate the performance of the developed model.

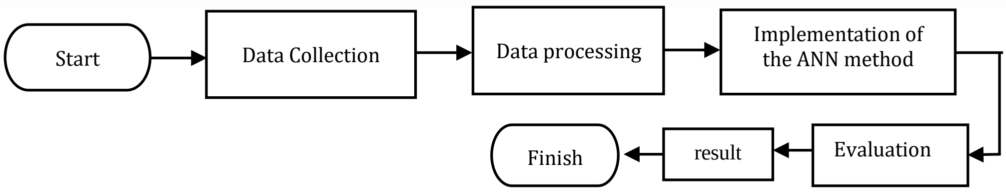

Figure 1. Diagram Alur Penelitian

Figure 1. shows the flow of research carried out, starting The collection of medical data in this study was obtained from the internet totaling 50 data from 2020-2021. next is Preprossing data by dividing datasets to be used as training and testing data and normalizing data. Furthermore, the implementation of the ANN method is by compiling the basic network structure on data. Finally, evaluation and results, analyzing the ability of the method has given the best percentage results.

Data Collection

Dengue fever medical record data230909- for 2020-2021 taken from the internet with a total of 50 patient data. The data included several variables such as date, name, gender, body temperature and other details of the patient's symptoms.

Data Pre-processing

The data will undergo a pre-processing process including dividing the dataset into two parts, namely 35 test data and 15 as test data and handling missing values. Normalization of data and encoding of categorical variables such as gender and the presence of red spots (El Khattabi et al., 2024). The data normalization formula can be written in equation (1).

$$x^{\iota} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where is the original value x, min x and max x is the maximum threshold of the feature, and x^{ι} is a normalized value.

Variable Selection and Model Optimization

Variable selection is carried out using statistical analysis techniques to identify the variables that are most significant to the diagnosis of DHF. Once variables are selected, model optimization steps are performed by adjusting network parameters, such as the number of hidden layers, the number of neurons per layer, and the learning rate, to achieve the best performance.

Algorithm Implementation

The ANN model will be implemented using Python. The network architecture will include an input layer corresponding to a variable number, a hidden layer, and an output layer that indicates the probability of dengue diagnosis.

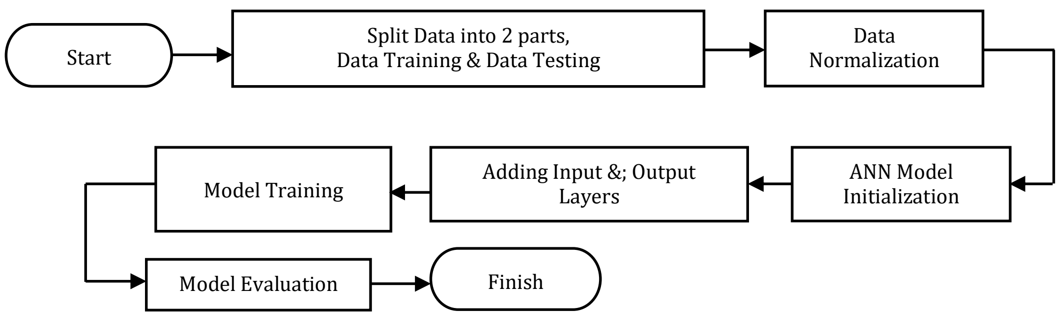

Figure 2. Implementation of ANN

Figure 2. Shows an Artificial Neural Network (ANN) implementation flowchart starting with dividing the dataset into training and testing sets, followed by data normalization to ensure consistency at feature scale. The next stage, the ANN model is initialized by specifying the architecture and paremeter. Once initialized, add an Input & Output layer to the specified network. The input layer that will receive the feature as well as the output layer generates a model prediction that has

diagnosed the patient with dengue fever or not (Shaikh et al., 2023). The formula adds an input output layer can be written in equation (2).

$$\alpha^{[L]} = f_L(W^{[L]} f_{L-1}(W^{[L-1]} \dots f_2 \left(W^{[2]} f_1 \left(W^{[1]} x + b^1\right) + b^2\right) \dots) + b^L \quad (2)$$

Where x is the input vector fed to the first layer of the network. The output of this layer, after the implementation of the *f1* function, becomes the input for the second layer. This process continues through various hidden layers, where each layer processes the input by combining weights and biases before applying the relevant activation functions. In the output layer marked with L, the final step of the transformation is performed by combining the activation of the previous layer ($L-1$) with the final weight, adding bias and using the last activation function f_L to produce the output. This output can be either a class prediction in the case of classification or an estimation of values for regression $\alpha^{[L]}$.

After that the training of the Artificial Neural Network (ANN) model is trained with training data, During this process the model learns to identify patterns and relationships in the data related to the presence or absence of dengue fever.

Model Evaluation

After the model is trained, then evaluate the model using the test dataset, then the model will display the results tested for validity using the confution matrix *Accuracy*, *Precicion, Recall, F1-Score* (Alem & Kumar, 2022). Each of these metrics provides a different perspective on the accuracy and effectiveness of the predictions generated by the model. The *Accuracy* Formula is written on the pad (3).

Accuracy is defined as the ratio of correct predictions, both positive and negative to the total number of cases in the dataset (Zhou et al., 2020).

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (3)$$

Where if TP is True Positive, i.e. the number of positive samples predicted correctly, TN is True Negative, i.e. the number of negative samples predicted correctly, FP is False Positive, i.e. the number of negative samples incorrectly predicted as positive, and FN is False Negative, i.e. the number of false positive samples predicted as negative. The formula for the precision equation is written in equation (4).

Precision is defined as the proportion of truly positive predictions. This metric is especially useful when FP costs are greater than FN (Obloj & Sengul, 2020).

$$Precision = \frac{TP}{(TP + FP)} \quad (4)$$

Where TP is True Positive, i.e. the number of positive samples correctly predicted by the model. FP is a False Positive, i.e. the number of negative samples that are incorrectly predicted as positive by the model. The Recall formula is written in equation (5). Recall is the ratio of all positive cases identified by the model (Chow et al., 2020).

$$Recall = \frac{TP}{(TP + FN)} \quad (5)$$

Where TP is True Positive, i.e. the number of positive samples correctly predicted by the model. FN is a False Negative, i.e. the number of positive samples incorrectly predicted as negative by the model. The F1 Score formula is written in equation (6).

The F1-Score is the harmonic average of precision and recall. F1-Score is used if there is an unbalanced distribution of classes (Hasib et al., 2023).

$$F1\ Score = \frac{2x(precisiom\ x\ Recall)}{(precisiom + Recall)} \tag{6}$$

Precision is a measure of the accuracy of positive predictions made by the model, calculated by formulas $\frac{\boldsymbol{TP}}{(\boldsymbol{TP+FP})}$, where TP is True Positive and FP is False Positive. Recall is used to measure the model's ability to identify all actual positive cases, calculated by formula $\frac{\boldsymbol{TP}}{(\boldsymbol{TP+Fn})}$, where FN is False Negative. Both of these metrics are important in evaluating the performance of classification models, especially in situations where the classes are out of balance.

Results and Discussions

The results obtained from the application of the ANN model are designed for early detection of Dengue Fever. Through detailed analysis of clinical data and the use of advanced machine learning techniques, the model has been tested for its ability to classify cases based on the presence of symptoms attributed to the disease. Model performance is represented through evaluative metrics such as *accuracy, precision, recall,* and *F1 Score*, demonstrating its effectiveness in identifying positive and negative cases. This discussion not only focuses on the interpretation of quantitative results achieved through model testing, but also explores the implications of such findings on clinical practice and the potential for further development in medical diagnostic technologies. In Table 1 the first step of data collection, in Table 2 the step of data normalization.

Table 1. Data on Dengue Fever Symptoms

No	Date	Name	Gender	Body Temperature (°Celsius)	Nausea Vomiting (times)	Joint Pain (day)	Lack of Appetite (days)	Dizziness (day)	Red Spot (Rash)	Diagnosis DBD
1	11/10/2020	Patient 1	L	38.2	2	2	1	5	Many	1
2	10/13/2020	Patient 2	P	39.1	3	2	4	1	Little	0
3	10/17/2020	Patient 3	P	42	1	1	3	2	Many	1
4	10/20/2020	Patient 4	L	40	4	2	6	2	Keep	0
5	10/21/2020	Patient 5	P	39.2	2	3	5	3	Many	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
46	11/2/2021	Patient 46	L	41.1	1	1	5	3	Many	1
47	2/13/2021	Patient 47	P	37.2	2	2	6	1	Many	1
48	2/16/2021	Patient 48	L	40.6	3	2	8	3	Keep	1
49	2/18/2021	Patient 49	L	39.4	0	4	1	2	Many	0
50	2/19/2021	Patient 50	L	38.6	3	5	5	3	Keep	1

Table 1. Presenting a complete dataset on Dengue Fever symptoms, which became the analytical basis in this study. This dataset includes clinical variables such as body temperature, nausea, joint pain, decreased appetite, headache, presence of skin rashes, and verified diagnostic results, covering a spectrum of Dengue cases from positive marked with the number 1 to negative marked with the number 0. This data collection is important because it provides basic input for training ANNs who have demonstrated outstanding performance in early detection of this disease. This ANN model was trained for 50 epochs to consistently improve on accuracy as well as decrease in loss value for both training and validation sets.

This performance is supported by comprehensive analysis performed by normalizing data, which is summarized in table 2. Normalization ensures that each contributing feature is evaluated fairly and consistently, allowing the model to focus on significant patterns rather than scale differences. This process is an important step that effectively prepares the data for analysis by the ANN model, then results in an accurate and reliable classification.

Table 2. Normalization Data

Feature	Min Value	Max Value
Body Temperature (Celsius)	-0.49	1.56
Nausea Vomiting (times)	-1.03	1.37
Joint Pain (day)	-1.16	-0.24
Lack of Appetite (days)	-1.08	2.52
Dizziness (day)	-0.95	1.27
Gender L	-0.92	1.09
Gender P	0.92	-1.09
Red spots (rashes) are numerous	1.22	1.22
Medium red spot (rash)	0.68	-0.68
Red spot (rash) slightly	-0.63	-0.63

Table 2. Shows a summary of normalized data used in model training and testing. Clinical features such as Body Temperature, Nausea, Vomiting, Joint Pain, Lack of Appetite, and Dizziness have been normalized to ensure consistency of scale in data analysis. Gender as well as Red Spot intensity are also included in normalization, with minimum and maximum values indicating the variation treated in the model. This data is crucial in optimizing the performance of the ANN model in detecting dengue cases more effectively.

The initialization stage of the model, the Artificial Neural Network (ANN) we developed using Hardware TensorFlow is governed by a multi-layer architecture. As depicted in the visualization in figure 3.

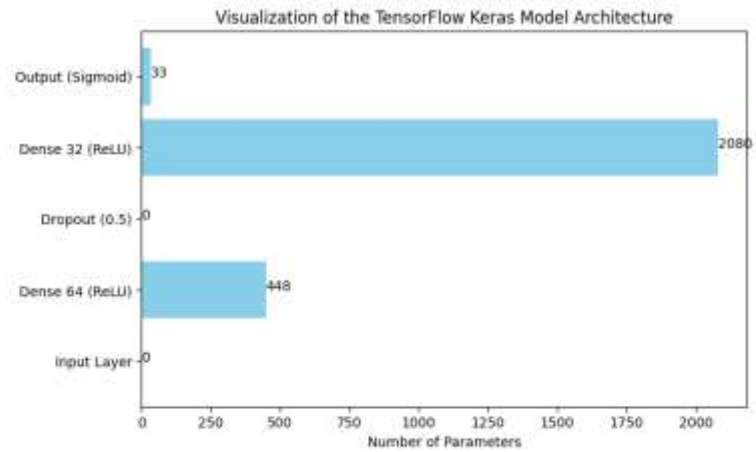

Figure 3. Inisialisasi Model

Figure 3. Explaining model initialization, it starts with an Input Layer that has no parameters and serves as an entry point for features that have been normalized. Furthermore, the first Dense Layer which has 64 neuron units uses the ReLU activation function and has 448 parameters. Then followed by a Dropout layer with a dropout rate of 0.5 to reduce the risk of overfitting. This layer does not add parameters to the model. The second Dense layer, which also uses ReLU activation, contains 32 units and contains 2,080 parameters. Finally, the Output Layer is defined with one unit using the Sigmoid activation function for binary classification, with 33 parameters. This structure allows the model to study complex data representations and classify dengue diseases more effectively. This process underscores the importance of proper architecture in predictive model development. Each layer is designed for progressive transformation from input to interpretable output, with a dropout layer providing a regularization mechanism to increase the generalizability of the model beyond the training sample. This architecture has proven effective, as illustrated in Figure 4.

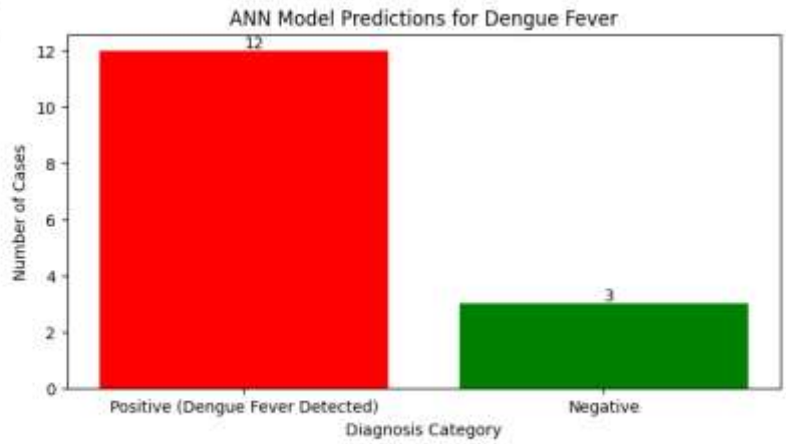

Figure 4. Result

Figure 4.Shows the display of the results of successful ANN implementation to classify Dengue Fever cases. By dividing two categories positive and negative based on red spot symptoms (rash). As seen in the graph above of the 15 cases tested, the ANN model successfully identified 12 cases as positive for regional fever and 3 cases as negative. The importance of these results lies in the model's ability to provide fast and accurate classification results, which can be very significant in improving treatment outcomes for patients. With reduced diagnosis time, medical interventions can be carried out faster, potentially saving lives and reducing the burden on health systems. This performance is reinforced by the evaluation results summarized in Table 3 which measures the effectiveness of the model in terms of *accuracy, precision, recall,* and *F1-Score.*

Table 3. Evaluation Model

Accuracy	Precision	Recall	F1-Score
0.87	0.92	0.92	0.92

Table 3. Shows the results of substantive evaluative metrics and reflects the comprehensive performance of the ANN model that has been implemented. The model recorded an accuracy of 0.87, indicating the overall effectiveness of the model in accurate classification. *A uniform precision, recall* and *F1-Score* of 0.92 indicates that the model is not only efficient in reducing false positive fallacies but also meticulous in identifying almost all actual positive cases in the test sample. The stability of this score confirms the reliability of the model in producing reliable classifications, crucial for clinical diagnostics where diagnostic precision has direct implications for treatment strategies and medical interventions.

This study developed an Artificial Neural Network (ANN) model for the early detection of Dengue Hemorrhagic Fever (DHF), showing significant performance in case classification based on symptoms. Unlike previous studies that used slow and less accurate conventional methods, this model provides faster and more precise diagnostics. Previous research in other fields has shown that similar approaches can improve prediction accuracy. In the medical context, this study has succeeded in improving the sensitivity and specificity of dengue diagnosis. In addition, this ANN model is more responsive to non-specific symptoms, filling gaps in previous research and offering innovative solutions for early detection of dengue, thereby improving patient care and outbreak control.

Conclusions

This study highlights the effectiveness of the Artificial Neural Network (ANN) method in the early detection of dengue fever, achieving high accuracy and precision. The developed ANN model is adaptable to local clinical data, enhancing its relevance for tropical and subtropical regions that face similar challenges in detecting these diseases. Implementing ANNs in resource-constrained areas can accelerate diagnostic accuracy, crucial for managing outbreaks. The research integrates machine learning with clinical data to improve early detection and provides a methodological framework applicable to other infectious diseases. Future research should expand the dataset, involve wider geographic variation, and use cross-validation to enhance the model's reliability in clinical practice, offering more comprehensive answers to posed research questions.

References

Al-Ani, A. H., Prentice, R. E., Rentsch, C. A., Johnson, D., Ardalan, Z., Heerasing, N., Garg, M., Campbell, S., Sasadeusz, J., & Macrae, F. A. (2020). prevention, diagnosis and management of COVID-19 in the IBD patient. *Alimentary Pharmacology & Therapeutics*, *52*(1), 54–72. https://doi.org/10.1111/apt.15779

Alem, A., & Kumar, S. (2022). Deep learning models performance evaluations for remote sensed image classification. *IEEE Access*, *10*, 111784–111793. https://doi.org/10.1109/ACCESS.2022.3215264

Ansari, A., Ahmad, I. S., Bakar, A. A., & Yaakub, M. R. (2020). A hybrid metaheuristic method in training artificial neural network for bankruptcy prediction. *IEEE Access*, *8*, 176640–176650. https://doi.org/10.1109/ACCESS.2020.3026529

Buonora, S. N., Passos, S. R. L., Daumas, R. P., Machado, M. G. L., Berardinelli, G. M., de Oliveira, D. N. R., & de Oliveira, R. de V. C. (2020). Pitfalls in acute febrile illness diagnosis: Interobserver agreement of signs and symptoms during a dengue outbreak. *Journal of Clinical Nursing*, *29*(9–10), 1590–1598. https://doi.org/10.1111/jocn.15229

Chow, J. K., Su, Z., Wu, J., Tan, P. S., Mao, X., & Wang, Y.-H. (2020). Anomaly detection of defects on concrete structures with the convolutional autoencoder. *Advanced Engineering Informatics*, *45*, 101105. https://doi.org/10.1016/j.aei.2020.101105

Chung, S. Y., & Abbott, L. F. (2021). Neural population geometry: An approach for understanding biological and artificial neural networks. *Current Opinion in Neurobiology*, *70*(November), 137–144. https://doi.org/10.1016/j.conb.2021.10.010

Cortés-Beringola, A., Vicent, L., Martín-Asenjo, R., Puerto, E., Domínguez-Pérez, L., Maruri, R., Moreno, G., Vidán, M. T., Arribas, F., & Bueno, H. (2021). Diagnosis, prevention, and management of delirium in the intensive cardiac care unit. *American Heart Journal*, *232*, 164–176. https://doi.org/10.1016/j.ahj.2020.11.011

El Khattabi, M.-Z., El Jai, M., Lahmadi, Y., Oughdir, L., & Rahhali, M. (2024). Understanding the interplay between metrics, normalization forms, and data distribution in K-means clustering: a comparative simulation study. *Arabian Journal for Science and Engineering*, *49*(3), 2987–3007. https://doi.org/10.1007/s13369-023-07741-9

Fauzi, I. S., Nuraini, N., Ayu, R. W. S., & Lestari, B. W. (2022). Temporal trend and spatial clustering of the dengue fever prevalence in West Java, Indonesia. *Heliyon*, *8*(8), e10350. https://doi.org/10.1016/j.heliyon.2022.e10350

Goes, F. R., Meerhoff, L. A., Bueno, M. J. O., Rodrigues, D. M., Moura, F. A., Brink, M. S., Elferink-Gemser, M. T., Knobbe, A. J., Cunha, S. A., & Torres, R. S. (2021). Unlocking the potential of big data to support tactical performance analysis in professional soccer: A systematic review. *European Journal of Sport Science*, *21*(4), 481–496. https://doi.org/10.1080/17461391.2020.1747552

Hanna, T. P., King, W. D., Thibodeau, S., Jalink, M., Paulin, G. A., Harvey-Jones, E., O'Sullivan, D. E., Booth, C. M., Sullivan, R., & Aggarwal, A. (2020). Mortality due to cancer treatment delay: systematic review and meta-analysis. *Bmj*, *371*. https://doi.org/10.1136/bmj.m4087

Hasib, K. M., Azam, S., Karim, A., Al Marouf, A., Shamrat, F. M. J. M., Montaha, S., Yeo, K. C., Jonkman, M., Alhajj, R., & Rokne, J. G. (2023). Mcnn-lstm: Combining cnn and lstm to classify multi-class text in imbalanced news data. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3309697

Kurucan, M., Özbaltan, M., Yetgin, Z., & Alkaya, A. (2024). Applications of artificial neural network based battery management systems: a literature review. *Renewable and Sustainable Energy Reviews*, *192*, 114262. https://doi.org/10.1016/j.rser.2023.114262

Li, Y., Dou, Q., Lu, Y., Xiang, H., Yu, X., & Liu, S. (2020). Effects of ambient temperature and precipitation on the risk of dengue fever: A systematic review and updated meta-analysis. *Environmental Research*, *191*, 110043. https://doi.org/10.1016/j.envres.2020.110043

Masi, F., Stefanou, I., Vannucci, P., & Maffi-Berthier, V. (2021). Thermodynamics-based Artificial Neural Networks for constitutive modeling. *Journal of the Mechanics and Physics of Solids*, *147*. https://doi.org/10.1016/j.jmps.2020.104277

Obloj, T., & Sengul, M. (2020). What do multiple objectives really mean for performance? Empirical evidence from the French manufacturing sector. *Strategic Management Journal*, *41*(13), 2518–2547.

https://doi.org/10.1002/smj.3198
Rathore, A. P. S., Farouk, F. S., & John, A. L. S. (2020). Risk factors and biomarkers of severe dengue. *Current Opinion in Virology*, *43*, 1–8. https://doi.org/10.1016/j.coviro.2020.06.008
Shaikh, M. S. G., SureshKumar, B., & Narang, G. (2023). Development of optimized ensemble classifier for dengue fever prediction and recommendation system. *Biomedical Signal Processing and Control*, *85*, 104809. https://doi.org/10.1016/j.bspc.2023.104809
Trenfield, S. J., Awad, A., McCoubrey, L. E., Elbadawi, M., Goyanes, A., Gaisford, S., & Basit, A. W. (2022). Advancing pharmacy and healthcare with virtual digital technologies. *Advanced Drug Delivery Reviews*, *182*, 114098. https://doi.org/10.1016/j.addr.2021.114098
Uwishema, O., Nnagha, E. M., Chalhoub, E., Nchasi, G., Mwazighe, R. M., Akin, B. T., Adanur, I., & Onyeaka, H. (2021). Dengue fever outbreak in Cook Island: A rising concern, efforts, challenges, and future recommendations. *Journal of Medical Virology*, *93*(11), 6073–6076. https://doi.org/10.1002/jmv.27223
Wong, J. M., Adams, L. E., Durbin, A. P., Muñoz-Jordán, J. L., Poehling, K. A., Sánchez-González, L. M., Volkman, H. R., & Paz-Bailey, G. (2022). Dengue: a growing problem with new interventions. *Pediatrics*, *149*(6), e2021055522. https://doi.org/10.1542/peds.2021-055522
Wu, T., Wu, Z., & Li, Y. (2022). Dengue fever and dengue virus in the People's Republic of China. *Reviews in Medical Virology*, *32*(1), e2245. https://doi.org/10.1002/rmv.2245n
Yang, L., Liu, C., Bi, P., Vardoulakis, S., & Huang, C. (2020). Local actions to health risks of heatwaves and dengue fever under climate change: Strategies and barriers among primary healthcare professionals in southern China. *Environmental Research*, *187*, 109688. https://doi.org/10.1016/j.envres.2020.109688
Zhong, N.-N., Wang, H.-Q., Huang, X.-Y., Li, Z.-Z., Cao, L.-M., Huo, F.-Y., Liu, B., & Bu, L.-L. (2023). Enhancing head and neck tumor management with artificial intelligence: Integration and perspectives. *Seminars in Cancer Biology*. https://doi.org/10.1016/j.semcancer.2023.07.002
Zhou, X., Lu, P., Zheng, Z., Tolliver, D., & Keramati, A. (2020). Accident prediction accuracy assessment for highway-rail grade crossings using random forest algorithm compared with decision tree. *Reliability Engineering & System Safety*, *200*, 106931. https://doi.org/10.1016/j.ress.2020.106931