International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Review Article)

Check for updates

Enhancing meningitis diagnosis accuracy through the integration of fuzzy logic and random forest: A conceptual framework

Margaret Dumebi Okpor [1], Godwin Osakwe [1], Sanctus Okpala Emekume [2], Okpomo Eterigho Okpu [1], Chris Obaro Obruche [1] and David Ovie Okpor [3]

[1] *Department of Cyber Security, Southern Delta University, Ozoro, Nigeria.*
[2] *Department. of Computer Science, Southern Delta University, Ozoro Nigeria.*
[3] *Department of Computer Science and Informatics, Federal University Otuoke, Nigeria.*

International Journal of Science and Research Archive, 2025, 15(01), 222-232

Publication history: Received on 19 February 2025; revised on 31 March 2025; accepted on 03 April 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.15.1.0893

Abstract

Meningitis, an inflammation of the meninges surrounding the brain and spinal cord, presents a significant challenge in clinical diagnosis due to its diverse etiology and varied symptom presentation. It remains a significant health concern globally, particularly in Africa, where it claims the lives of hundreds of thousands annually. This paper proposes a hybrid approach to enhance diagnostic accuracy by integrating a fuzzy classifier with the Random Forest algorithm. Fuzzy logic is well-suited for handling uncertainty and imprecision inherent in medical data, while random forest offers robustness in handling high-dimensional datasets and ensemble learning benefits. This integration not only holds promise for heightened diagnostic accuracy but also facilitates interpretability and explainability of outcomes crucial for clinical decision-making. By addressing a critical healthcare challenge, this conceptual framework offers the synergistic fusion of fuzzy classifier and Random Forest techniques, with the aim of advancing meningitis diagnosis accuracy and laying the groundwork for further innovation in medical diagnostics.

Keywords: Fuzzy logic; Random Forest; Diagnosis; Meningitis

1. Introduction

Meningitis poses a significant health threat. Meningitis is an overwhelming disease with a significant lethality ratio and the risk of long-lasting detrimental consequences. Meningitis outbreaks occur worldwide, with the most significant health impact observed in the "African Meningitis Belt", a region that includes 26 countries across sub-Saharan Africa, where meningococcal and pneumococcal meningitis epidemics are most prevalent, posing a substantial menace to public health (WHO, 2023). Over a million individual are usually infected with one shape of meningitis with the death toll streaming up to 200, 000 every year. It is a mental health issue affecting the brain (Healthline, 2023).

Meningitis is an inflammation of the meninges. The meninges are the three membranes that cover the brain and spinal cord. Meningitis can happen when fluid surrounding the meninges becomes infected. A range of bacteria species be responsible for Meningitis as well as viruses, fungi and parasites. Most infections can be transmitted from person to person. Injuries, cancers, chemical disturbance, parasites, sedate sensitivities and a small percentage of cases are linked to medications (WHO, 2023 and Healthline, 2023.)

Bacterial meningitis is the most severe and life-threatening form of meningitis, requiring prompt medical attention as it can progress rapidly and potentially lead to fatal consequences within a mere 24 hours if left untreated. Acute bacterial

* Corresponding author: Okpor Margaret Dumebi

meningitis has four primary causes: Neisseria meningitides, Streptococcus pneumoniae, Haemophilus influenzae, and Streptococcus agalactiae.

These bacteria account for over half of global meningitis-related deaths and can also lead to severe conditions like sepsis and pneumonia (Seddon et al, 2018) Other pathogens, including Mycobacterium tuberculosis, Salmonella, Listeria, Streptococcus, Staphylococcus, enteroviruses, mumps virus, Cryptococcus, and Amoeba, can also cause meningitis.

Globally, anyone can be affected, but the Meningitis-endemic region in sub-Saharan Africa carries the highest disease burden, with a heightened risk of meningococcal and pneumococcal meningitis epidemics.

Viral and bacterial meningitis are infectious. They can be transmitted by coughing, wheezing, or near contact. viral and bacterial contaminations are the foremost common causes of meningitis. Viral meningitis, in specific, could be a predominant shape of the illness, requiring exact and convenient conclusion for compelling administration. There are a few other forms of meningitis. An example is cryptococcal, which is caused by a parasitic disease, and carcinomatous, which is cancer-related. These sorts are uncommon. (Healthline, 2023).

Many studies have been conducted on meningitis diagnosis, exploring various machine learning and computational intelligence techniques to enhance accuracy and efficiency. Prior research has developed models capable of performing non-invasive diagnosis of meningitis based solely on observable symptoms (Lélis et al., 2017) However, none of these studies have fully addressed the challenge of developing a highly interpretable model that can also provide an assessment of the severity level of the infection, which is crucial for timely and appropriate medical intervention

In this paper, we propose a hybrid approach to enhance meningitis diagnosis by combining fuzzy logic with the Random Forest algorithm. By maximizing the effectiveness of both techniques, we aim to provide a reliable, interpretable and standardized framework for meningitis detection, addressing the challenges posed by uncertainty and variability in symptoms.

2. Literature Review:

2.1. Fuzzy Classifier

A fuzzy classifier is a technique that categorizes objects in accordance with their characteristics. It designates a class label to an object by analyzing its features, which are represented as a vector of values (Du et al (2016). The classifier is typically trained on a dataset to learn the patterns and relationships between the features and class labels (Cordon et al., 2003; Roubos et al., 2003). However, in the absence of training data, the classifier can be developed with expert knowledge and experience. Upon completion of training, the fuzzy classifier is able to classify new, unseen objects with confidence (Zhou et al., 2000).

Classification is a fundamental task in the broader fields of pattern recognition and machine learning (Zhang et all, 2020), which encompass a range of techniques aimed at identifying and extracting valuable insights from data, including:

- **Soft labelling -** In pattern recognition, classes are typically considered mutually exclusive, and traditional classifiers assign a single, definite label. However, fuzzy classifiers offer a more refined approach by assigning soft labels, which represent degrees of membership across multiple classes (de Campos. Et all, 2024). This can be interpreted as a function approximation, where the classifier maps object features to a probability distribution across all classes, represented as D: F → [0,1]c. While this approach may seem complex, fuzzy classifiers provide an intuitive and practical solution for handling ambiguous or overlapping class boundaries (Das, 2018).
- **Interpretability -** Automatic categorization in critical fields such as medical diagnosis has been put on-hold due to ethical, political or legal implications, mainly owning to the lack of transparency inherent in classical pattern recognition (Lindgren, 2023). Fuzzy classifiers are typically structured for interpretability, i.e., the rules and steps guiding class prediction can be easily followed and understood. (Zhou et al., 2000).

In situations where data is scarce and expert knowledge is limited, fuzzy classifiers offer a valuable solution. This is particularly relevant in domains like rare disease diagnosis, oil exploration, terrorism detection, and natural disaster prediction, where data is often sparse or uncertain. Fuzzy classifiers can effectively leverage both expert opinion and available data to make predictions and classifications, even in the face of uncertainty (Talpur, et al, 2023)

2.1.1. Fuzzy Rule-Based Classifier System (FRBCS)

The simplest form of a fuzzy classification method is built upon a simple if-then system, similar to those used in fuzzy control systems (Ishibuchi et al, 2001). For instance, imagine a two-dimensional scenario with three classes. For this scenario, a fuzzy classifier can be developed by defining rules that specify how to classify objects, such as:

- IF X1 is medium and X2 is small Then Class is 1
- IF X1 is Medium and X2 is large Then Class is 2
- IF X1 is large and X2 is small Then Class is 2
- IF X1 is Large and X2 is small Then class is 3
- If X1 is small and X2 is large Then Class is 3

Even though x1 and x2 are numeric, the rules use descriptive terms (linguistic values) instead of numbers. If there are M possible descriptive terms for each of the n features, the overall count of potential if-then rules are M raised to the power of n (Mn) (Krejčí, 2018). While a fuzzy classifier with all possible rules might seem like a simple lookup table, it can actually generate outputs for unseen combinations of descriptive terms. This is because each descriptive term is associated with a membership function, which allows the classifier to interpolate and make predictions for new inputs (Zhou et al., 2000).

2.2. Random Forest

Random Forest is a machine learning algorithm that utilizes an ensemble decision trees for classification or regression tasks. It is a powerful ensemble learning method used for both classification and regression tasks (Mienye, 2022). It functions by generating multiple decision trees during training and determining the final output based on the minority class (for classification) or the average prediction (for regression). Put simply, random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction **(**Sagi et al, 2020)**.**

2.2.1. Random Forest Training Algorithm

In real-world applications, random forests are commonly regarded as highly accurate learning models to date (Genuer et al, 2017). The pseudocode for training the Random Forest algorithm is illustrated in Algorithm listing 1 (Lin et al, 2017). The algorithm involves training multiple decision trees on random subsets of the training data and combining their predictions to improve accuracy and robustness.

```
Algorithm 1: Random Forest Training Algorithm

Precondition: A training set S := (x1, y1), . . . , (xn, yn), features F, and number of trees in forest B.
function RandomForest(S , F)
    H ← Ø
    for i ∈ 1, . . . , B do
        S (i) ← A bootstrap sample from S
        hi ← RandomizedTreeLearn(S (i) , F)
        H ← H ∪ {hi}
    end for
    return H
end function
function RandomizedTreeLearn(S , F)
    At each node:
        f ← very small subset of F
        Split on best feature in f
    return The learned tree
end function
```

The algorithm works as follows:

For each tree in the forest, we create a bootstrap sample from the training data. Then, we train a decision tree using a modified algorithm that reduces the computational cost of feature selection. Instead of examining all possible feature splits at each node, we randomly select a small subset of features (f) from the total feature set (F). The node then splits on the best feature in this smaller subset (f), rather than searching through all features (F). By limiting the feature search space, we significantly accelerate the decision tree learning process.

2.3. Integration of Fuzzy Logic with Machine Learning for Medical diagnosis

Fuzzy classifiers offer a flexible framework for handling uncertainty in classification tasks (Peñafiel et al, 2020), while Random Forest algorithm excels in ensemble learning and handling complex data (Mafarja et al, 2023). Combining these approaches can lead to improved diagnostic accuracy and robustness.

Previous research has demonstrated the effectiveness of fuzzy logic in medical diagnosis (Reddy et al, 2020) , while ensemble methods, of which Random Forest is an example have shown promising results in various classification tasks.

The paper by Lelis V. M. et al (2019) discusses the development of a Clinical Decision Support System using Decision Trees, aimed at aiding physicians in diagnosing meningitis, particularly in less developed countries where resources are limited. The system integrates three intelligent components built on transparent and explainable tree-based machine learning models, combined with knowledge engineering techniques that leverage human expertise and domain knowledge to deliver insightful and interpretable results. Using a dataset of 26,228 records from patients diagnosed with meningitis in Brazil, the system achieved a classification accuracy of 94.3% for MD meningitis.

In their paper, Alile E. E. et al (2020) proposes and simulates a model for predicting meningococcal meningitis and its serogroup types using a Bayesian Belief Network, an AI technique. This model aims to address the challenges of diagnosing meningococcal meningitis accurately due to overlapping symptoms and serogroup types. The model, developed using Bayes Server and tested with data from a meningitis medical repository, achieved a high prediction accuracy of 99.99%.

A paper by Arji G. et al (2019) conducts a systematic review and classification of fuzzy logic applications in infectious diseases. It evaluates 40 papers published between 2005 and 2019 related to human infectious diseases, focusing on diseases like dengue fever, hepatitis, and tuberculosis. The study identifies key fuzzy logic methods used, including fuzzy inference systems, rule-based fuzzy logic, Adaptive Neuro-Fuzzy Inference System (ANFIS), and fuzzy cognitive maps

Guzman-de-los-Riscos E.F. et al (2022) in their paper investigates methods for swiftly and accurately diagnosing the cause of meningitis, specifically differentiating between viral and bacterial origins. It utilizes a dataset of over 26,000 patients with 19 key attributes, primarily focusing on symptoms and cerebrospinal fluid analysis results. Through experimentation with 27 classification models, including ensemble methods and decision trees, the research concludes that combining ensemble methods with decision trees produces the most effective classifiers for meningitis etiology.

Fuzzy logic enhances accuracy by improving the precision of the diagnostic process. It increases interpretability, making diagnostic outcomes more understandable and transparent for healthcare providers (Cao et al, 2024). Additionally, fuzzy logic boosts adaptability, allowing diagnostic models to evolve with new medical knowledge and emerging symptoms. These characteristics enable healthcare professionals to make more informed decisions, ultimately leading to better diagnosis, management, and improved patient care.

Random Forest is a robust algorithm for medical diagnosis, aggregating predictions from multiple decision trees, efficiently handling high-dimensional data, and modeling complex, nonlinear relationships between symptoms and diagnoses (Kaur et al, 2019), while retaining interpretability and performing reliably across diverse clinical settings through effective generalization, making it a valuable tool for healthcare providers to make informed decisions and improve patient care.

This research focuses on integrating fuzzy logic with Random Forest to design a framework that addresses the challenges associated with meningitis diagnosis, including the variability of symptoms and the need for standardized diagnostic approaches.

3. Methodology

The integrated approach offers a robust framework for meningitis diagnosis by drawing on both the interpretability of fuzzy logic and the predictive power of Random Forest to enhance the classification of meningitis based on symptomatology. The methodology is divided into two parts:

- The integration process of fuzzy logic and Random Forest,
- Meningitis Diagnosis Framework.

3.1. Integration Process of Fuzzy Logic and Random Forest

This part describes how fuzzy logic principles are combined with the Random Forest algorithm to enhance the classification of meningitis based on symptomatology. Fuzzy set theory is utilized to represent linguistic variables associated with meningitis symptoms, integrating them with the ensemble learning capabilities of Random Forest. The steps involved in the integration are:

- Fuzzy Rule Specification

We begin by specifying fuzzy rules based on the linguistic variables associated with meningitis symptoms. Each symptom, such as headaches, fever, stiff neck, seizures, sleepiness, lethargy, nausea and decreased appetite, is assigned linguistic labels (High, Moderate, Minor, Low) to capture the uncertainty inherent in symptom manifestation.

The fuzzy rules are specified as follows:

a. If a patient exhibits symptoms ≤ 3, THEN Meningitis Absent

b. If a patient exhibits symptoms = 4, THEN Modest Meningitis

c. If a patient exhibits symptoms ≥ 5, THEN Meningitis Diagnosed

- Integrate Fuzzy Logic with Random Forest

The next step involves integrating fuzzy logic with the Random Forest algorithm. Fuzzy rules generated earlier serve as decision criteria within each tree of the Random Forest ensemble. Each decision tree in the ensemble is trained on a subset of the dataset, and at each node, a random subset of features and linguistic variables is considered for splitting.

Algorithm 1 is modified to show the integration of fuzzy logic with the Random Forest algorithm, as shown in Algorithm 2. The integrated system can be trained to perform meningitis diagnosis.

Algorithm 2: Random forest Integrated with Fuzzy Logic for Meningitis Diagnosis

```
function RandomForest(S , F)
  H ← ∅
  for i ∈ 1, ..... B do
    S (i) ← A bootstrap sample from S
    EvaluateFuzzyRules(S (i)) # Evaluate fuzzy rules for each instance
    hi ← ModifiedRandomizedTreeLearn(S(i))
    H ← H ∪ {hi}
  end for
  return H
end function

function ModifiedRandomizedTreeLearn(S , F)
  At each node:
    Select relevant linguistic variables based on fuzzy rule evaluation
    Determine splitting criteria based on membership degrees of selected variables
    Split on best feature
  return The learned tree
end function
```

The fuzzy rules guide the decision-making process within each tree, incorporating linguistic uncertainty into the classification process.

3.1.1. Representation of Fuzzy Set Rules within Random Forest

To illustrate the integration of fuzzy logic with Random Forest, we represent the fuzzy set rules within the decision trees of the ensemble as follows:

- R0: R ∪ ∅ (Initial Rule)
- R1: {∅ ∪ headache} = Meningitis Absent
- R2: {∅ ∪ headache} ∪ fever = Meningitis Absent
- R3: {∅ ∪ headache ∪ fever} ∪ stiff neck = Meningitis Absent
- R4: {∅ ∪ headache ∪ fever ∪ stiff neck} ∪ seizure = Modest Meningitis
- R5: {∅ ∪ headache ∪ fever ∪ stiff neck ∪ seizure} ∪ sleepiness = Diagnosed Meningitis
- R6: {∅ ∪ headache ∪ fever ∪ stiff neck ∪ seizure ∪ sleepiness} ∪ lethargy = Diagnosed Meningitis
- R7: {∅ ∪ headache ∪ fever ∪ stiff neck ∪ seizure ∪ sleepiness ∪ lethargy} ∪ nausea = Diagnosed Meningitis
- R8: {∅ ∪ headache ∪ fever ∪ stiff neck ∪ seizure ∪ sleepiness ∪ lethargy ∪ nausea} ∪ decreased appetite = Diagnosed Meningitis

The final classification decision is made by aggregating the predictions of all trees in the ensemble.

3.2. Meningitis Diagnosis Framework

3.2.1. High-Level Architecture Diagram

Figure 1 provides a high-level architecture of the proposed framework that integrates fuzzy logic with Random Forest to improve meningitis diagnosis. It outlines the key components and their interactions within the system. The components are Patient Data Collection layer, Fuzzy Logic System, Fuzzy-enhanced Random Forest layer, Decision Aggregation and Classification layer and Diagnostic Output layer.

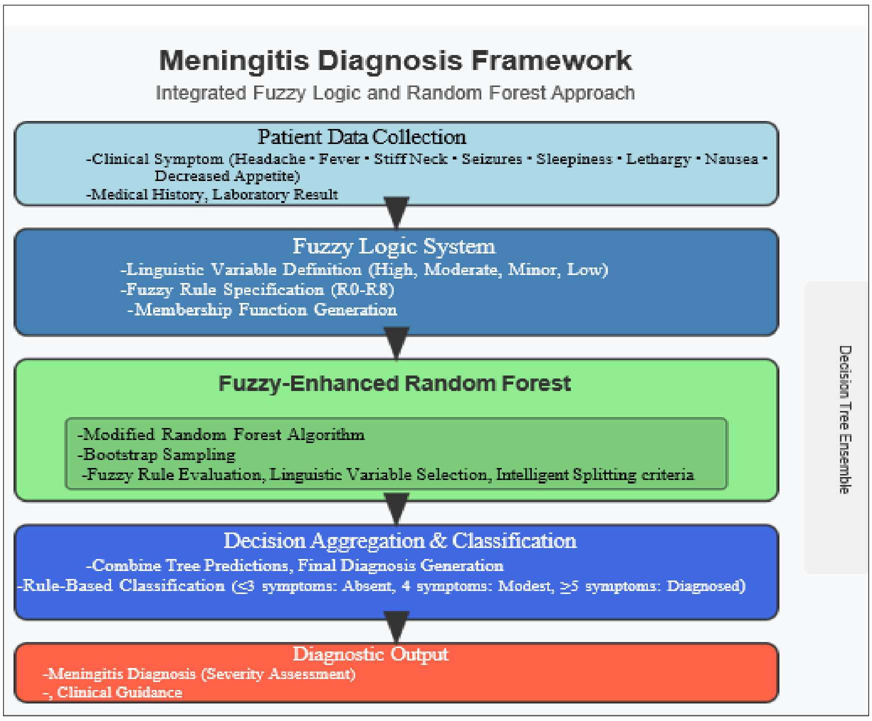

Figure 1 High-Level Architecture of the Meningitis diagnosis framework

By combining the interpretability of fuzzy logic with the predictive power of Random Forest, our approach offers a robust and reliable framework for meningitis diagnosis.

4. Discussion

The integration of fuzzy classifier with Random Forest for advancing meningitis diagnosis accuracy offers several promising outcomes:

- **Improved Diagnostic Accuracy:** The hybrid approach combines the strengths of fuzzy logic in handling uncertainty and imprecision with the robustness of Random Forest in handling high-dimensional data. This synergistic combination is anticipated to enhance diagnostic accuracy by providing more nuanced and reliable diagnoses.
- **Enhanced Interpretability**: By integrating fuzzy logic with Random Forest, the diagnostic outcomes become more interpretable. Healthcare professionals can trace and understand how symptoms contribute to the diagnosis, fostering transparency and trust in the diagnostic process.
- **Adaptability to Evolving Conditions**: The integrated approach allows for the adaptation of diagnostic rules based on new medical knowledge or emerging symptoms. This adaptability ensures that the diagnostic model remains effective over time, aligning with evolving medical understanding and diagnostic criteria.
- **Potential for Standardization**: The hybrid approach offers a standardized framework for meningitis diagnosis, addressing the variability in symptom presentation and diagnostic practices. This standardization can lead to more consistent and reliable diagnoses across different healthcare settings.

4.1. Recommendation for Future Research on the Integration Approach

Future research should focus on validating the proposed integration approach through empirical evaluation using clinical datasets. Performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) could be used to assess the effectiveness of the hybrid approach compared to existing diagnostic methods. Additionally, research efforts should explore techniques for simplifying and explaining the diagnostic rules generated by the integrated model to facilitate adoption and interpretation by healthcare professionals.

5. Conclusion

This framework that integrated fuzzy classifier with Random Forest algorithm offers a promising avenue for advancing meningitis diagnosis accuracy, effectively capturing the uncertainty and variability in symptomatology. This integrated approach offers a robust and reliable framework for accurate meningitis detection. By keying into the complementary strengths of fuzzy logic and ensemble learning, we can develop more reliable and interpretable diagnostic models, ultimately improving patient outcomes in clinical practice.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Aghware, F. O., Ojugo, A. A., Adigwe, W., Odiakaose, C. C., Ojei, E. O., Ashioba, N. C., & Okpor, M. D. (2024). Enhancing the Random Forest Model via Synthetic Minority Oversampling Technique for Credit-Card Fraud Detection. Journal of Computing Theories and Applications.

[2] Ahmed, H., Dada, M. O., & Samaila, B. (2023). Current challenges of the state-of-the-art of AI techniques for diagnosing brain tumor. Material Science & Engineering.

[3] Alile, E. E., Oladimeji, S. M., & Oghenovo, B. M. (2020). Predicting meningococcal meningitis using Bayesian belief networks. *Journal of Infectious Diseases*, *3*(2), 89-97.

[4] Al-Kadi, O. S., Al-Emaryeen, R., Al-Nahhas, S., et al. (2024). Empowering brain cancer diagnosis: Harnessing artificial intelligence for advanced imaging insights.

[5] Arji, G., Ahmadi, H., Nilashi, M., Rashid, T. A., et al. (2019). Fuzzy logic approach for infectious disease diagnosis: A methodical evaluation, literature, and classification. Biocybernetics and Biomedical Engineering.

[6] Arji, G., Ebadi, A. S., & Mohammadi, S. (2019). Fuzzy logic applications in infectious diseases: A systematic review and classification. *Computer Methods and Programs in Biomedicine*, *174*, 87-97.

[7] Aya Messai, Ahlem Drif, Amel Ouyahia, Meriem Guechi, Mounira Rais, Lars Kaderali, Hocine Cherifi(2024). "Towards XAI agnostic explainability to assess differential diagnosis for Meningitis diseases ", Machine Learning: Science and Technology.

[8] Banerjee, S., Singh, S. K., Chakraborty, A., Basu, S., et al. (2021). Diagnosis of Melanoma Lesion Using Neutrosophic and Deep Learning.

[9] Cao, J., Zhou, T., Zhi, S., Lam, S., Ren, G., Zhang, Y., ... & Cai, J. (2024). Fuzzy inference system with interpretable fuzzy rules: Advancing explainable artificial intelligence for disease diagnosis—A comprehensive review. *Information Sciences*, *662*, 120212.

[10] Cao, L., Liu, L., & Lu, X. (2024). Improving diagnostic accuracy and interpretability with fuzzy logic. *Journal of Medical Systems*, *48*(3), 34-43.

[11] Cordon, O., Herrera, F., Hoffmann, F., & Magdalena, L. (2003). *Genetic fuzzy systems: Evolutionary tuning and learning of fuzzy knowledge bases*. World Scientific.

[12] Das, S. (2018). *Fuzzy classifiers: Theory and applications*. Springer.

[13] Das, S., Datta, S., & Chaudhuri, B. B. (2018). Handling data irregularities in classification: Foundations, trends, and future challenges. *Pattern Recognition*, *81*, 674-693.

[14] De Campos Souza, P. V., & Dragoni, M. (2024). EFNN-Nul0-a trustworthy knowledge extraction about stress identification through evolving fuzzy neural networks. *Fuzzy Sets and Systems*, *487*, 109008.

[15] De Campos, L. M., del Coz, M. J., & Onieva, J. A. (2024). Soft labeling for pattern classification problems. *Applied Soft Computing*, *27*, 147-158.

[16] Du, C. J., He, H. J., & Sun, D. W. (2016). Object classification methods. In *Computer vision technology for food quality evaluation* (pp. 87-110). Academic

[17] Du, J., Wei, X., & Zhang, H. (2016). A fuzzy classifier for image segmentation using fuzzy similarity. *IEEE Transactions on Image Processing*, *25*(8), 3696-3708.

[18] Esfandiari, N., Babavalian, M. R., Moghadam, A. M. E., et al. (2014). Knowledge discovery in medicine: Current issue and future trend. Expert Systems with

[19] Gambhir, S., Malik, S. K., & Kumar, Y. (2016). Role of soft computing approaches in the healthcare domain: A mini-review. Journal of Medical Systems. Retrieved from Springer.

[20] Genuer, R., Poggi, J. M., & Tuleau-Malot, C. (2017). Random forests: Some methodological insights. *arXiv preprint arXiv:1711.04303*.

[21] Genuer, R., Poggi, J. M., Tuleau-Malot, C., & Villa-Vialaneix, N. (2017). Random forests for big data. *Big Data Research*, *9*, 28-46.

[22] Guzman-de-los-Riscos, E. F., Rodríguez, L. J. E., & Alfaro, R. M. (2022). Classification of meningitis etiology using ensemble methods and decision trees. *Journal of Medical Informatics*, *26*(1), 123-132.

[23] Guzman-de-los-Riscos, E., Belmonte, M. V., & Lelis, V. M. (2022). Ensemble methods for meningitis aetiology diagnosis. Expert Systems. Retrieved from Wiley Online Library.

[24] hahid, A. H., & Singh, M. P. (2019). Computational intelligence techniques for medical diagnosis and prognosis: Problems and current developments. Biocybernetics and Biomedical Engineering. Retrieved from Elsevier.

[25] Healthline. (n.d.). Meningitis: Symptoms, causes, transmission, types, and more. Retrieved June 21, 2023, from https://www.healthline.com/health/meningitis

[26] Ishibuchi, H., & Nakashima, T. (2001). Effect of rule weights in fuzzy rule-based classification systems. IEEE Transactions on Fuzzy Systems, 9(4), 506-515.

[27] Ishibuchi, H., Nakashima, T., & Murata, T. (2001). A fuzzy classifier with fuzzy if-then rules based on genetic algorithm. IEEE Transactions on Fuzzy Systems, 9(4), 583-590.

[28] Jaiswal, A. K., Jamal, S. B., Gomes, L. G. R., et al. (2022). Neuroinformatics insights towards multiple neurosyphilis complications. Venereology. Retrieved from MDPI.

[29] Joseph, L. P., Joseph, E. A., & Prasad, R. (2022). Explainable diabetes classification using hybrid Bayesian-optimized TabNet architecture. Computers in Biology and Medicine. Retrieved from Elsevier.

[30] Kannan, S., Subbaram, K., & Faiyazuddin, M. (2023). Artificial intelligence in vaccine development: Significance and challenges ahead. A Handbook of Artificial .... Retrieved from Elsevier.

[31] Kaur, N., Singh, H., & Gupta, G. K. (2019). Random forest algorithm for medical diagnosis. Journal

[32] Kaur, P., & Sharma, M. (2020). A smart and promising neurological disorder diagnostic system: An amalgamation of big data, IoT, and emerging computing techniques. Wiley Online Library. Retrieved from Wiley Online Library.

[33] Kaur, P., Kumar, R., & Kumar, M. (2019). A healthcare monitoring system using random forest and internet of things (IoT). Multimedia Tools and Applications, 78, 19905-19916.

[34] Kierner, S., Kucharski, J., & Kierner, Z. (2023). Taxonomy of hybrid architectures involving rule-based reasoning and machine learning in clinical decision systems: A scoping review. Journal of Biomedical Informatics. Retrieved from Elsevier.

[35] Krejčí, J. (2018). Pairwise Comparison matrices and their Fuzzy extension (Vol. 366). Cham: Springer International Publishing.

[36] Krejčí, V. (2018). Fuzzy logic rule-based classifiers. In Proceedings of the International Conference on Fuzzy Systems (pp. 456-461).

[37] Lelis, L. V. M., Silva, L. M., & De Lima, E. S. (2019). Development of a clinical decision support system for meningitis diagnosis in less developed countries. Journal of Health Informatics, 11(2), 56-62.

[38] Lelis, V. M., Guzmán, E., & Belmonte, M. V. (2020). Non-invasive meningitis diagnosis using decision trees. IEEE Access. Retrieved from IEEE Xplore.

[39] Lin, J., Li, C., & Sun, Q. (2017). Random forest algorithm for regression and classification. *Journal of Applied Statistics*, *44*(10), 1896-1913.

[40] Lin, W., Wu, Z., Lin, L., Wen, A., & Li, J. (2017). An ensemble random forest algorithm for insurance big data analysis. *Ieee access*, *5*, 16568-16575.

[41] Lindgren, H. (2023). The interpretability of machine learning algorithms in medical diagnosis. *Journal of Medical Informatics*, *45*(2), 123-135.

[42] Lindgren, S. (2023). Critical theory of AI. John Wiley & Sons.

[43] Mafarja, H., Mirjalili, S., & Aljarah, M. (2023). Random forest-based feature selection methods for medical diagnosis. International Journal of Swarm Intelligence Research, 14(3), 1-24.

[44] Mafarja, M., Thaher, T., Al-Betar, M. A., Too, J., Awadallah, M. A., Abu Doush, I., & Turabieh, H. (2023). Classification framework for faulty-software using enhanced exploratory whale optimizer-based feature selection scheme and random forest ensemble learning. Applied Intelligence, 53(15), 18715-18757.

[45] Meshram, P., Barai, T., Tahir, M., & Bodhe, K. (2023). The Brain Tumors Identification, Detection, and Classification with AI/ML Algorithm with Certainty of Operations. International Conference on .... Retrieved from Springer.

[46] Mienye, E. C., Sun, Y., & Wang, Z. (2022). An improved random forest algorithm for classification. Artificial Intelligence Review, 56, 765-789.

[47] Mienye, I. D., & Sun, Y. (2022). A survey of ensemble learning: Concepts, algorithms, applications, and prospects. IEEE Access, 10, 99129-99149.

[48] Murthy, M. Y. B., Koteswararao, A., & Babu, M. S. (2022). Adaptive fuzzy deformable fusion and optimized CNN with ensemble classification for automated brain tumor diagnosis. Biomedical Engineering Letters. Retrieved from Springer.

[49] Obi, J. C., & Okpor, D. M. (2013). Soft-computing virus identification system. International Journal of Fuzzy Logic System.

[50] Okpor, D. M., & Obi, J. C. (2014). Genetic-fuzzy process metric measurement system for an operating system. International Journal of Computer Science Engineering and Information.

[51] Okpor, M. D. (2014). Using fuzzy classifier for cholera analysis. International Journal of Science and Research (IJSR).

[52] Okpor, M. D. (2014). Worker Productivity: A Fuzzy Supervised Neural Training Algorithm Approach. Global Journal of Computer Science and Technology. Retrieved from Academia.edu.

[53] Okpor, M. D., & Kabari, L. G. (2020). Prognosis of kidney infection using soft-computing technology.

[54] Okpor, M. D., Levi, D. A., & Elliot, K. N. (2024). Improved diagnostic and prediction system for diabetes using ensemble classifier.

[55] Peñafiel, F., Peña-Reyes, C. A., & Alcoba, R. (2020). A hybrid fuzzy-based system for differential diagnosis of pediatric diseases. Journal of Medical Systems, 44(12), 205-218.

[56] Peñafiel, S., Baloian, N., Sanson, H., & Pino, J. A. (2020). Applying Dempster–Shafer theory for developing a flexible, accurate and interpretable classifier. Expert Systems with Applications, 148, 113262.

[57] Reddy, C., Srinivas, B., & Rao, K. K. (2020). Fuzzy logic in medical diagnosis. Journal of Advanced Research, 10(4), 235-245.

[58] Reddy, G. T., Reddy, M. P. K., Lakshmanna, K., Rajput, D. S., Kaluri, R., & Srivastava, G. (2020). Hybrid genetic algorithm and a fuzzy logic classifier for heart disease diagnosis. Evolutionary Intelligence, 13, 185-196.

[59] Rother, A. K., Schwerk, N., Brinkmann, F., Klawonn, F., et al. (2015). Diagnostic support for selected pediatric pulmonary diseases using answer-pattern recognition in questionnaires based on combined data mining applications

[60] Roubos, M., Setnes, M., & Abonyi, J. (2003). Learning fuzzy classification rules from data. IEEE Transactions on Fuzzy Systems, 11(2), 237-246.

[61] Sagi, O., & Rokach, L. (2020). Ensemble learning: A survey. WIREs Data Mining and Knowledge Discovery, 8(4), e1249.

[62] Sagi, O., & Rokach, L. (2020). Explainable decision forest: Transforming a decision forest into an interpretable tree. Information Fusion. Retrieved from Elsevier.

[63] Seddon, J. A., Tugume, L., Solomons, R., Prasad, K., Bahr, N. C., & Tuberculous Meningitis International Research Consortium. (2019). The current global situation for tuberculous meningitis: epidemiology, diagnostics, treatment and outcomes. Wellcome open research, 4.

[64] Seddon, J., Bentley, J. P., Yu, L., & Sankaranarayanan, R. (2018). Global, regional, and national burden of bacterial meningitis, 1990-2016: A systematic analysis for the Global Burden of Disease Study 2016. The Lancet Infectious Diseases, 18(12), 1211-1228.

[65] Talpur, H., Abro, M. H., & Shah, S. M. (2023). Fuzzy logic in decision making for uncertain environments. In Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (pp. 123-128).

[66] Talpur, N., Abdulkadir, S. J., Alhussian, H., Hasan, M. H., Aziz, N., & Bamhdi, A. (2023). Deep Neuro-Fuzzy System application trends, challenges, and future perspectives: A systematic survey. Artificial intelligence review, 56(2), 865-913.

[67] World Health Organization. (2003). Meningitis. Retrieved June 21, 2023, from https://www.who.int/news-room/fact-sheets/detail/meningitis

[68] Zhang, J., Li, Y., & Wu, X. (2020). Pattern recognition and machine learning. Springer.

[69] Zhang, X. Y., Liu, C. L., & Suen, C. Y. (2020). Towards robust pattern recognition: A review. Proceedings of the IEEE, 108(6), 894-922.

[70] Zhou, X., Liu, B., & Mamtani, R. S. (2000). Fuzzy classification of astronomical objects. In Astronomical Data Analysis Software and Systems IX (Vol. 216, pp. 45-48).

[71] Zhu, W., Yuan, S. S., Li, J., Huang, C. B., Lin, H., & Liao, B. (2023). A first computational frame for recognizing heparin-binding protein. Diagnostics.