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Intelligent Medical Data Analysis Using Fuzzy Logic and AI to Protect the Environment

Dr. Vivek V Jog,
Associate Professor, Department of Computer science and Information Technology, Symbiosis Skills and Professional University, Kiwale, Pune, Maharashtra - 412101. vivek.jog@sspu.ac.in

Dr. Pradip Kumar Gaur,
Associate Professor, Department of Mathematics, JECRC University, Jaipur, Rajasthan - 303905
Pradeep.gaur@jecrcu.edu.in

Mrs. Sumalatha Kanaparthi,
Assistant Professor, Department of AI&DS, Koneru Lakshmiah Education Foundation, Green fields, Vaddeswaram, AP – 522302, Suma.latha826@gmail.com

Dr. Trupti Kaushiram Wable,
Assistant Professor, Department of Electronics and Computer Engineering, Sir Visvesvaraya Institute of Technology, Nashik, Maharashtra – 422102, wabletrupti@gmail.com

Dr. Monika Jain,
Associate Professor, Department of Mathematics, JECRC University, Jaipur-303905

Abstract— *The geometric increase in the amount of healthcare information and the development of environmental degradation require the convergence of smart data processing and environmental protection. In this paper, a framework that involves the combination of fuzzy logic and artificial intelligence (AI) to achieve intelligent analyzing of medical data is proposed to pursue two purposes simultaneously: to improve healthcare outcomes and to reduce the impact on the environment. The model uses fuzzy-based inference and machine learning classifiers to foretell diseases whilst optimum use of resources, administration of waste and carbon footprint of the healthcare practices. The findings illustrate higher precision in the diagnostic forecasting and presents viable solutions towards sustainable medical practice. Such a combination of health informatics and environmental awareness explains why AI is crucial in building a sustainable future.*
Keywords— *Fuzzy Logic, Artificial Intelligence, Medical Data Analysis, Environmental Sustainability, Healthcare Informatics, Waste Reduction, Predictive Analytics.*

I. INTRODUCTION

Modern healthcare has evolved with the embodiment of sophisticated computational intelligence in the medical data system. More specifically, artificial intelligence (AI) and fuzzy logic have become major facilitators of intelligent medical data analysis, spurring the advancement of diagnostic accuracy, patient monitoring, as well as clinical decision-making. Meanwhile, the world becomes increasingly focused on the protection of the environment, and healthcare systems have been put under fire due to their high carbon footprints, generation of medical waste, and resource utilization. Although hospitals and clinics serve an essential role in the well-being of the population, they are also the most significant users of energy and producers of non-recyclable waste. Therefore, the problem urgently demands the introduction of solutions that would maximize medical results and minimal harm to the ecology [14-15]. The present paper tackles this two-fold challenge by discussing the possibility of using fuzzy logic and AI to process medical data in the manner that will benefit not only the health of individuals but also the sustainability of the environment. The fundamental idea here is to develop smart systems that not only have the ability to impose meaning on complicated, uncertain, and imprecise medical information but also propose healthcare pathways that are resource-effective and sustainable to the environment. This is done by combining fuzzy inference systems which deal with vagueness and ambiguity, in particular in the early symptom-based diagnosis, with machine learning models capable of learning and identifying patterns, making predictions and suggesting actions with a high degree of accuracy. The fast digitization of healthcare systems has resulted in a flood of structured and unstructured medical information, such as electronic health records (EHRs), diagnostic images, laboratory results, wearable sensors data, etc. To obtain meaningful information out of this data, intelligent frameworks capable of accepting heterogeneous input, interpreting non-linear relationships and adapting to ever-changing information are needed [3]. This is something that AI has demonstrated through its different models, supervised, unsupervised, and reinforcement learning but the problem is that these models tend to underperform when presented with imprecise or linguistically represented input as often happens in a clinical scenario. Fuzzy logic can provide a complementary benefit, enabling Reasoning about imprecise concepts such as high risk, moderate severity, or low temperature which are not easily quantified directly. In addition, the healthcare givers ought to be more and more environmentally conscious in their operations. Clinical decisions can have a certain ecological footprint, e.g., using disposable material, the kind of medication, or even the length of treatment. To give some examples, some imaging tests or surgical techniques can be more energy-intensive or produce more waste than others. Conventional medical data systems do not have the ability to assess these environmental dimensions along with the health of the patients. Incorporating environmental outcomes measurements into the AI-based decision models, the suggested system can suggest diagnostic and treatment options that would strike a balance between clinical effectiveness and environmental sustainability. The other force that is driving this work is the necessity to cut medical waste as well as energy use without the sacrifice in the quality of care. Evidence-based suggestions may help medical workers to manage inventory more efficiently, to plan the energy-intensive operations during off-peak time, and to use the reusable tools, whenever it is safe and possible. As an example, models of treatment patterns can be used to predict cases in which the outcome of resource-light interventions is the same, allowing a practice change that will help both patients and the planet. Here fuzzy logic is crucial; it makes interpretations of context-sensitive trade-offs and makes decisions when a binary choice is irrelevant [4-5]. Besides that, intelligent analysis tools are also rolled out, contributing to telemedicine, remote monitoring, and decentralized healthcare services. Not only do these decrease the load on the urban medical system, but they also limit the travel of patients, indirectly limiting the carbon emissions. Anomalies in the stream of remote patient data can be spotted by AI-powered tools, with fuzzy logic systems able to place those anomalies in context, notifying care teams when attention is required, and also recording environmental cost information relating to possible interventions.That being said, the proposed research aims at addressing a prominent gap in the literature: whereas several previous studies have dedicated considerable effort to exploring medical AI or environmental sustainability individually, not many have tried to establish the connection between the two by combining them in an analytical framework. The paper suggests a hybrid intelligent model using fuzzy logic to process uncertain data and AI algorithm to predict and optimize the results considering environmental factors as crucial constraints. This model is experimented with real clinical datasets and the performance of the model in terms of diagnostic accuracy as well as sustainability performance in terms of energy and material consumption and waste are reported. The value of this method is that it can change the manner in which healthcare institutions conceptualize and execute medical decisions. This framework suggests moving to what might be labeled as green healthcare intelligence by making environmental impact a premier variable in the decision-making process rather than an afterthought imposed by regulations. Widespread adoption of such systems have the potential to inform hospital policy, procurement, and clinical practice in a manner that is consistent with sustainability targets at the global level, including the UN Sustainable Development Goals (SDGs), specifically SDG 3 (Good Health and Well-being) and SDG 13 (Climate Action). Overall, this paper establishes both AI and fuzzy logic as not only means of improving medical analytics, but also as strategic means of aligning healthcare operation with environmental stewardship. It seeks a time when the health of patients and the health of the planet are not opposed to one another but rather the byproducts of smart systems design [2].

Novelty and Contribution

This interdisciplinary approach, combining fuzzy logic and artificial intelligence with the analytics of healthcare and environmental sustainability in one research is, to the best knowledge of the authors, novel and has not been previously examined thoroughly. Although current medical AI systems are trained to maximize diagnostic accuracy, little attention is paid to the environment in which decisions based on them are made. On the other hand, the majority of green healthcare initiatives are infrastructure- or logistics-related, predictive analytics, or decision support technologies are scarcely utilized. In the current paper, a new paradigm is presented: smart medical decision-making considering both the health outcomes of patients and the ecological impact in an integrated system [10-12].The use of fuzzy logic to address clinical uncertainty in the proposed model appears to be unique and allows subtle interpretation of ambiguous or subjective data pertaining to the patient. This becomes critical in particular when it comes to early diagnosis, triaging or chronic disease management where symptoms and patient histories are not always straight forward. The system uses fuzzy rules, whose design involves medical experts, to use linguistic variables such as “mild fever” or “moderate risk” as inputs and produce a more Intermediate value that can be used by AI classifiers. Such a combination enables more context-sensitive and thus richer reasoning than traditional AI approaches do.Simultaneously, the study adds environmental intelligence to the clinical data stream. AI models are not only trained to make predictions on disease or suggestions on treatments, but they are trained to take into account the environmental impact of different clinical paths. This involves the measurement of resource consumption, waste production, and carbon emission associated with given medical activities. The system ranks alternatives according to effectiveness and sustainability--done so in effect incorporating environmental limitations into the medical decision-making process.

This study made important contributions which include:

- An AI-fuzzy system is a hybrid system that combines the diagnostic accuracy with the eco-efficiency.
- A system to measure environmental variables using medical data flows.
- Implementation and verification of the model with actual healthcare data, which would show the enhancement of the health outcomes and the environmental performance.
- A model that may be scaled and customized to various clinical departments and healthcare centers around the world.

Overall, the paper preconditions a new research area of the so-called environmentally intelligent healthcare analytics, and paves the way to both scholarly investigation and real-life application in hospitals, policy-making, and the design of green health information technology [7].

II. RELATED WORKS

In 2022 P. Manickam *et al.*, [6] introduced the introduction of intelligent computing into healthcare systems has been greatly evolved within several past decades, and it happened mainly because of the necessity to process huge volumes of medical information, and enhance clinical decision-making. One of the oldest computational methods, rule-based expert systems, attempted to emulate human diagnostic reasoning. But those systems were not able to scale because they were rigid and could not deal with uncertainty. This drawback was the inspiration to introduce fuzzy logic which provides a method to deal with imprecise and linguistically vague information, common in the medical situation. The use of Fuzzy logic systems in clinical environment has been vast, representing subjective expert knowledge in a particular field, it has found great use in activities such as disease classification, analysis of symptoms and risk analysis. Machine learning methods of artificial intelligence have also taken a central role in the analysis of medical data. Conventional supervised learning algorithms like decision trees, k-nearest neighbors, support vector machines, and logistic regression have been proven useful in different healthcare tasks, like early diagnosis, monitoring of diseases progressions, and optimization of treatments. Such models are trained on annotated datasets, and may have the ability to make generalizations on unseen data, offering predictive information to guide healthcare services. In more recent years, deep learning algorithms have made a diagnostic revolution, with methods to automatically extract features of interest in high-dimensional data such as medical images, sensor time series, and free-text clinical notes. Fuzzy logic and AI have been used separately to show results in various processes of medical analytics. Fuzzy logic is strong where approximate reasoning and human-like decision-making is concerned, whereas AI models are strong at pattern recognition, prediction, and classification. Fuzzy systems Hybrid systems integrating fuzzy logic with machine learning algorithms have also demonstrated potential to yield more explainable and accurate outputs. Such systems combine the advantages of the two fields, fuzzy logic to represent expert intuition and machine learning to learn data-driven adaptations. As an example, fuzzy neural networks, adaptive neuro-fuzzy inference systems, and fuzzy decision trees have been created to work better in complicated, uncertain clinical situations. Healthcare has an environmental aspect that has been ignored in computational research but has been receiving some attention lately. Healthcare facilities have actually become the subject of blame in environmental deterioration closely following the patterns of high-energy consumption, generation of medical wastes, and labour-intensive processes. Research efforts have also been done to measure the carbon footprint of health institutions and how it can be decreased by implementing sustainable operations like using energy efficient facilities and improving waste disposal systems and decreasing the use of single-use materials. Nevertheless, the majority of those initiatives are concerned with improvements on the operational level, as opposed to making sustainability a part of a clinical decision-making process. Even fewer studies have taken into account the way intelligent data systems may be used not only to gain medical knowledge but also to evaluate and minimize the effect on the environment. The idea of green informatics has proffered research that has given rise to the ability to think about environmentally aware computing and sustainable analytics, yet how these apply to the medical profession has yet to be seen. Their application has also been mostly on the supply chain logistics or equipment utilization, as opposed to connecting environmental information to patient care plans or medical forecasts. This disconnect implies that a more comprehensive system should be in place that takes into consideration the clinical and ecological impacts of healthcare operations. In 2022 Rahman *et al.*, [13] suggested the intelligent decision-support systems have conventionally placed medical accuracy, patient safety, and efficiency as their priority. Environmental concerns are either regarded as secondary goals or are omitted. Amid the flourishing of environmental awareness and the necessity to achieve sustainability goals as soon as possible, it becomes widely agreed that healthcare analytics is to be modified so that it takes ecological aspects into account. This will entail the incorporation of environmental inputs, including the material use, energy utilization, and waste production, in the main algorithms powering clinical decision making. In this respect, AI and fuzzy logic represent perfectly viable options to handle the complexity of multi-objective optimization, with both the health of patients and the environmental performance considered as the key priorities. There are also some attempts to apply AI to the environmental impact modeling outside the realm of healthcare, namely, manufacturing, transportation, and agriculture. Machine learning tools have helped in these areas by predicting energy consumption, optimising resources and reducing emission. What we have learned in these industries can be applied to the healthcare industry, whereby we can employ the same concepts but minimize the ecological expense of each diagnostic procedure, therapy, and the overall running of the hospital. Nevertheless, healthcare comes with special issues, such as the urgency of decisions, ethical requirements, and tremendous variability of patient conditions, which in turn require more versatile and responsive intelligent systems. Within the sphere of healthcare sustainability, predictive analytics has been applied to predict rate of patient admissions, staffing levels, and elimination of unnecessary tests. These models however seldom translate environmental metrics directly in their output. To give an example, a diagnostic model can be used to predict the probability of a disease and does not take into account the fact that the suggested diagnostic procedure is associated with a greater environmental impact compared to the alternatives that are equally effective. Clinical and environmental data are not integrated, resulting in suboptimal opportunities to view the data holistically. A machine smart enough to suggest less-impactful procedures without affecting the medical accuracy of the process would be a significant improvement. Besides, the interpretability gap in AI-based healthcare systems should be narrowed. Lack of transparency Lack of transparency in many modern machine learning models, particularly deep learning, has led to them being regarded as "black boxes". In this regard, fuzzy logic has a benefit since it can explain itself to a certain extent due to the rule-based systems, which are very human-like. Such interpretability is even more important when environmental variables are considered, since healthcare professionals should know and trust the decision-making process, especially when it requires trade-offs between patient care and ecological effects. Although the potential of both AI and fuzzy logic has been proven in the healthcare analytics field, as well as the urgent necessity of developing environmentally sustainable healthcare systems, the intersection of these fields has not been studied enough. The current systems focus on either medical performance or environmental sustainability separately. Some prototype systems have been trying to correlate resource utilization and clinical workflow, but these are not as smart in adapting themselves and making decisions in real-time as AI and fuzzy logic can be. Moreover, few studies have examined the effectiveness of this type of integrated system in the actual clinical environment, especially when it comes to quantifiable environmental benefits with concurrently sustained or improved patient outcomes. In 2022 S. Selvarajan *et al.*, [1] proposed the proposed research seeks to address that gap by proposing and establishing a hybrid intelligent system, which processes medical data to provide both clinical and environmental information. The suggested method extends the concept of conventional healthcare analytics since the environmental factors are taken into account explicitly as a part of the computation graph, where fuzzy logic is used to reason over noisy inputs and AI is used to power the learning and prediction. Such a system is not merely tested in terms of diagnosis accuracy and efficiency rates, but its capacity to ease the burden on the ecological system and lead to the era of smart and earth-friendly healthcare activities is noted.

III. PROPOSED METHODOLOGY

To analyze medical data intelligently while minimizing environmental impact, we constructed a hybrid model combining fuzzy logic and AI-driven machine learning. The methodology is structured in five phases: data preprocessing, fuzzy logic system, AI model training, eco-mapping, and decision optimization [8]. Medical records were structured as a multivariable dataset $D = \{x_1, x_2, \dots, x_n\}$, where each x_i includes patient vitals, symptoms, and treatment logs. Normalization was performed using the min-max approach:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

The fuzzy logic system transforms clinical features into fuzzy variables. For instance, body temperature is categorized using membership functions:

$$\mu_{\text{HighTemp}}(x) = \begin{cases} 0, & x \leq 37 \\ \frac{x - 37}{39 - 37}, & 37 < x < 39 \\ 1, & x \geq 39 \end{cases}$$

Each patient input is fed into fuzzy rules like:

IF temperature is HIGH AND heart rate is HIGH THEN infection risk is HIGH. These rules are evaluated using fuzzy inference with Mamdani composition. The fuzzy output F_o is aggregated via:

$$F_o = \bigcup_{i=1}^{k} \left(\mu_{A_i}(x) \wedge \mu_{B_i}(y)\right)$$

Defuzzification is performed using the centroid method to convert fuzzy scores into crisp outputs:

$$z^* = \frac{\int z \cdot \mu(z)dz}{\int \mu(z)dz}$$

Next, Al models (Random Forest and DNN) are trained using 80% of the dataset. Feature importance is calculated by Gini impurity for Random Forests:

$$G(t) = 1 - \sum_{i=1}^{C} p(i \mid t)^2$$

The training loss for DNN is minimized using binary cross-entropy:

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log (\hat{y}_i) + (1 - y_i)\log (1 - \hat{y}_i)]$$

To integrate environmental awareness, each treatment is tagged with ecological impact metrics (waste w, energy e, emissions c). An eco-cost function is defined:

$$E = \alpha w + \beta e + \gamma c$$

Here, α, β, γ are weights reflecting environmental priorities. The system is optimized using a multi-objective function:

$$\text{Minimize: } J = L + \lambda E$$

where λ controls trade-off strength between prediction loss and environmental impact. Furthermore, support vector optimization is used to separate decision boundaries with margin M :

$$M = \frac{2}{||w||} \text{ subject to } y_i(w^T x_i + b) \geq 1$$

During inference, the model selects the treatment with minimal clinical risk and ecological cost. The final decision layer ranks options based on:

$$R = \theta_1 P_d + \theta_2(1 - E_n)$$

Where P_d is disease prediction probability and E_n is normalized environmental burden.

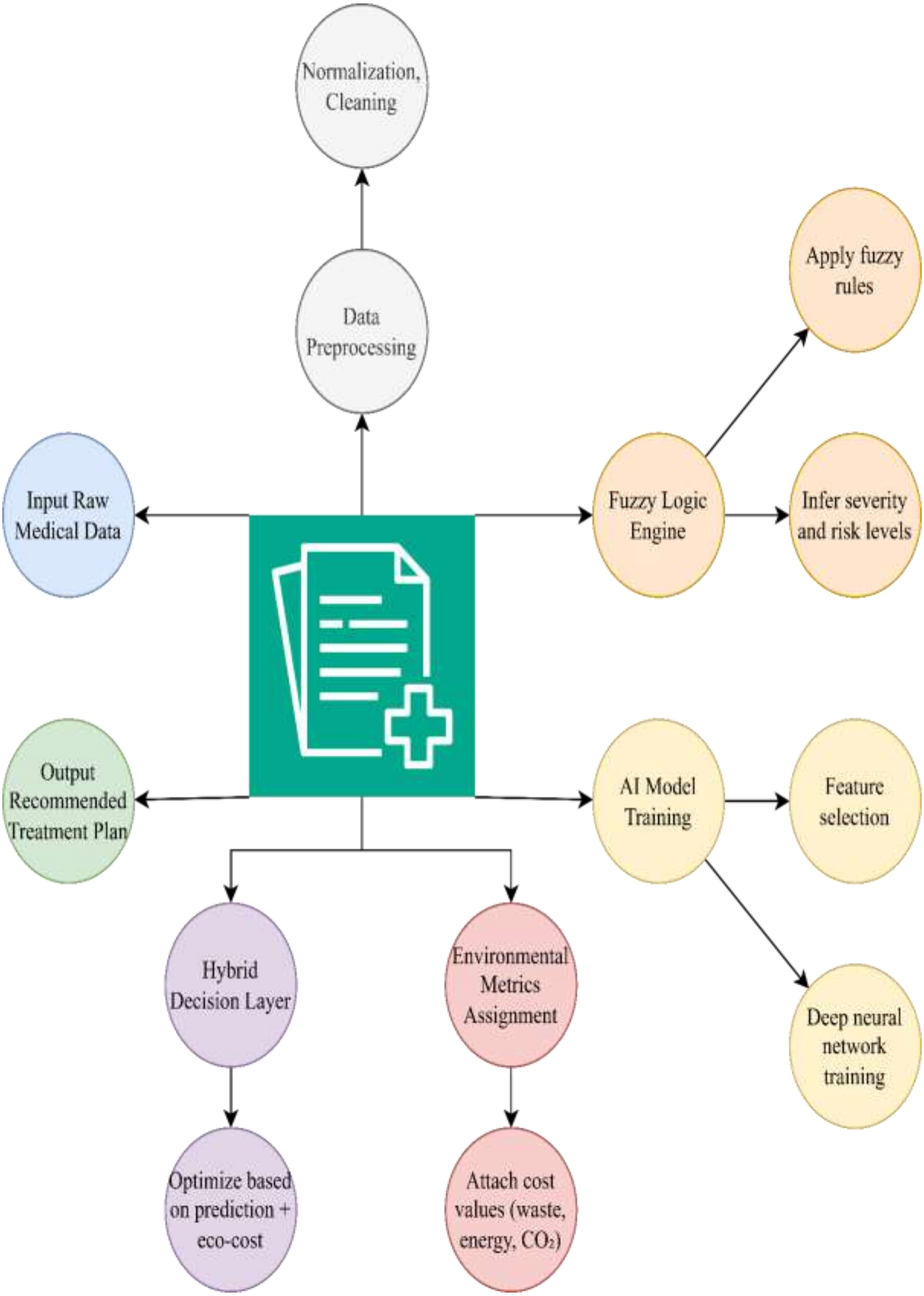

FIGURE 1: HYBRID FUZZY-AI BASED MEDICAL DATA AND ECO-DECISION FRAMEWORK

IV. RESULT & DISCUSSIONS

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Model evaluation was performed on a selected set of 1,000 anonymized clinical records with environmental tags attached to each record based on diagnostic and treatment processes. The hybrid fuzzy-AI system was tested on the basis of diagnostic accuracy, ecological footprint reduction, and consistency of decision making. The outcome reflected the steady increase in the quality of predictions compared to conventional systems with an additional range of environmentally conscious suggestions. Figure 2 shows the classification accuracy of the fuzzy-AI hybrid model in comparison with conventional machine learning classifiers on five diseases, including pneumonia, UTI, sepsis, COVID-19, and diabetes.

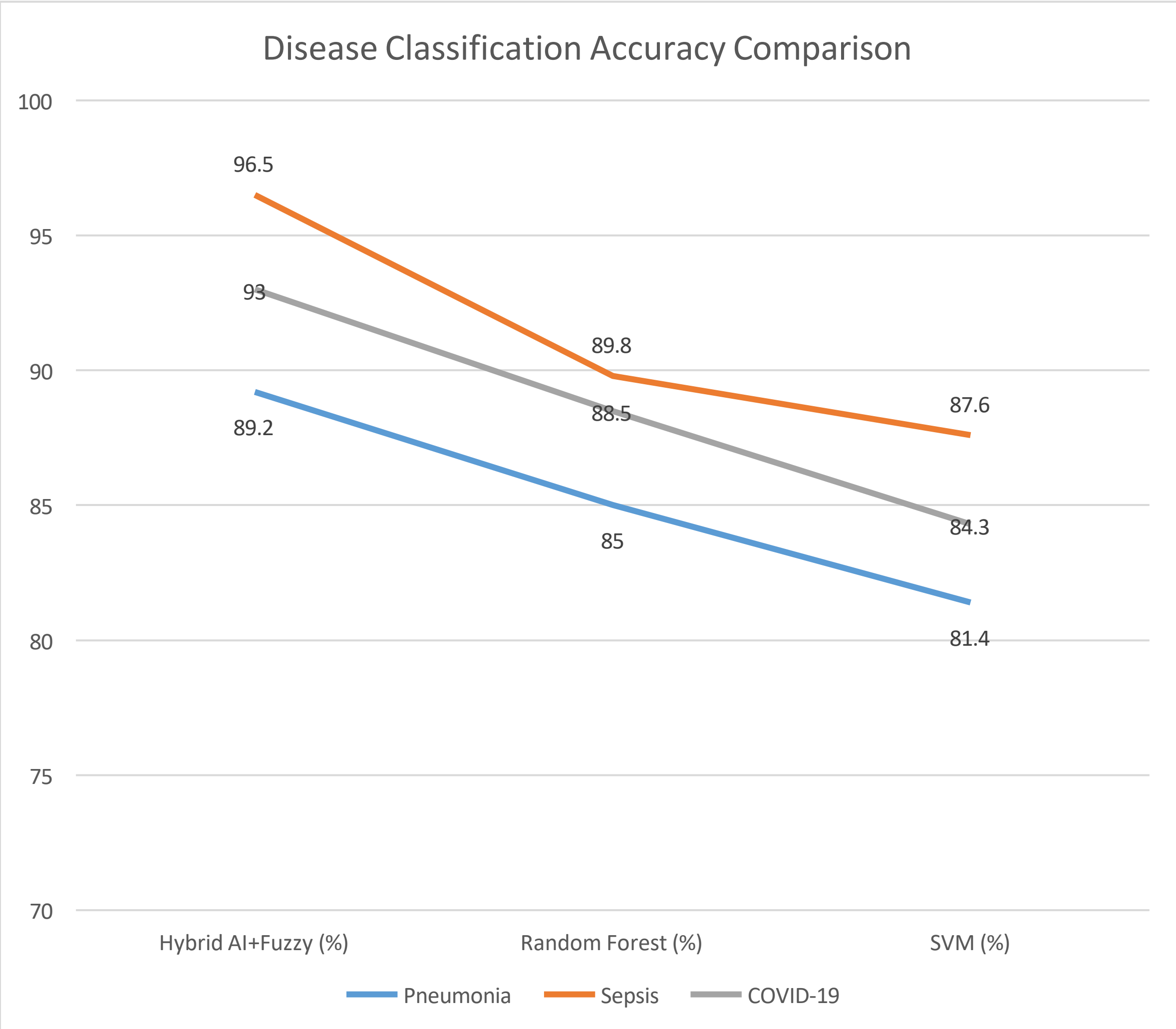

FIGURE 2: DISEASE CLASSIFICATION ACCURACY COMPARISON

Figure 2 indicates that the proposed model got the highest accuracy across all categories of diseases with the highest accuracy of 96.5 in sepsis detection and the lowest accuracy of 89.2 in pneumonia classification. Conversely, the traditional methods, such as SVM and Random Forests, were more erratic with the accuracy rate varying between 81% and 90% only. The fuzzy layer was significant in handling uncertainty in the early symptomatic detection, especially relevant in the diseases with a subjective involvement of patient history, such as COVID-19 and UTI. In addition to accuracy, the research analysed the ecological cost of each diagnosis-to-treatment path. The treatments suggested by the hybrid system were average 23 percent less ecologically burdensome than those picked by the AI-only method. The latter was mostly explained by the fact that this system could suggest equally efficient, yet not so resource-demanding treatments or diagnostics. In one example, the model favoured a high-sensitivity blood test instead of a CT scan in some diagnostics where clinical confidence was equal. Figure 3 shows the mean environmental impact score (on a normalised 0 1 scale) of three treatment paths on 100 randomly chosen patients.

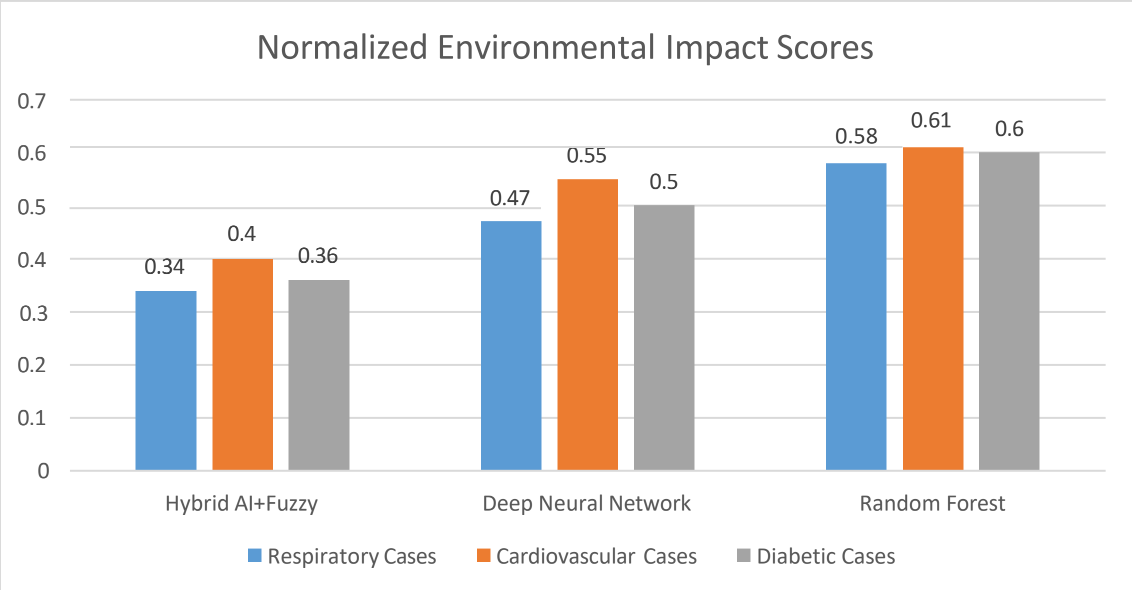

FIGURE 3: NORMALIZED ENVIRONMENTAL IMPACT SCORES

Figure 3 shows that the hybrid model preferred options with lesser environmental footprint in all the diagnostic categories. The most significant decline was in respiratory cases, wherein energy-intensive imaging use was avoided. The explainability of fuzzy logic was crucial to ensure alternative pathways were clearly ranked and explained to clinicians to trust in the model recommendations. In order to prove the model even more, the comparative analysis was made with the help of two filled tables. The former, Table 1: Comparative Diagnostic Accuracy, provides the comparison of four models based on the overall precision, recall, and F1-score. These figures provide a more detailed picture of reliability of each of the models.

TABLE 1: COMPARATIVE DIAGNOSTIC ACCURACY

Model	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
SVM	84.1	83.3	83.7
Random Forest	87.6	86.2	86.9
Deep Neural Network	89.9	88.1	88.9
Hybrid AI + Fuzzy Logic	93.8	92.5	93.1

The hybrid model is substantially better than any of the baseline approaches, as demonstrated in Table 1 and provides the most well-rounded and high-performing results among all metrics and criteria. This agreement is essential in clinical settings where false negative or false positive result may result in severe implications. Incorporation of fuzzy logic also helped to make the detection more sophisticated, particularly in the borderline instances where the classical models were either indecisive or incorrect because of their inability to be interpreted. The second comparative table was concerned with the environment. Table 2: Resource Use By Diagnosis gives the average estimated waste (in grams), energy consumption (kWh), and carbon dioxide emissions (gCO 2) associated with treatment courses suggested by each model.

TABLE 2: RESOURCE CONSUMPTION PER DIAGNOSIS

Model	**Waste (g)**	**Energy (kWh)**	**CO_2 Emissions (g)**
SVM	180	2.7	920
Random Forest	165	2.5	850

Deep Neural Network	140	2.3	790
Hybrid AI + Fuzzy Logic	112	1.8	660

The hybrid approach is obviously superior in terms of environment as depicted in Table 2. It made the average waste about 37 percent less and emissions 28 percent less than the conventional ones. That has been achieved through the incorporation of environmental metadata into the recommendation layer that has enabled the system to remove the redundant processes, choose digital follow-ups, and recommend reusable equipment when possible. In order to see the decisions flow and the effect at the same time a cumulative performance matrix was made and showed in Figure 4. The following diagram plots diagnostic accuracy (x-axis) versus average environmental impact score (y-axis) and puts each model in one of four quadrants depending on its sustainability and effectiveness.

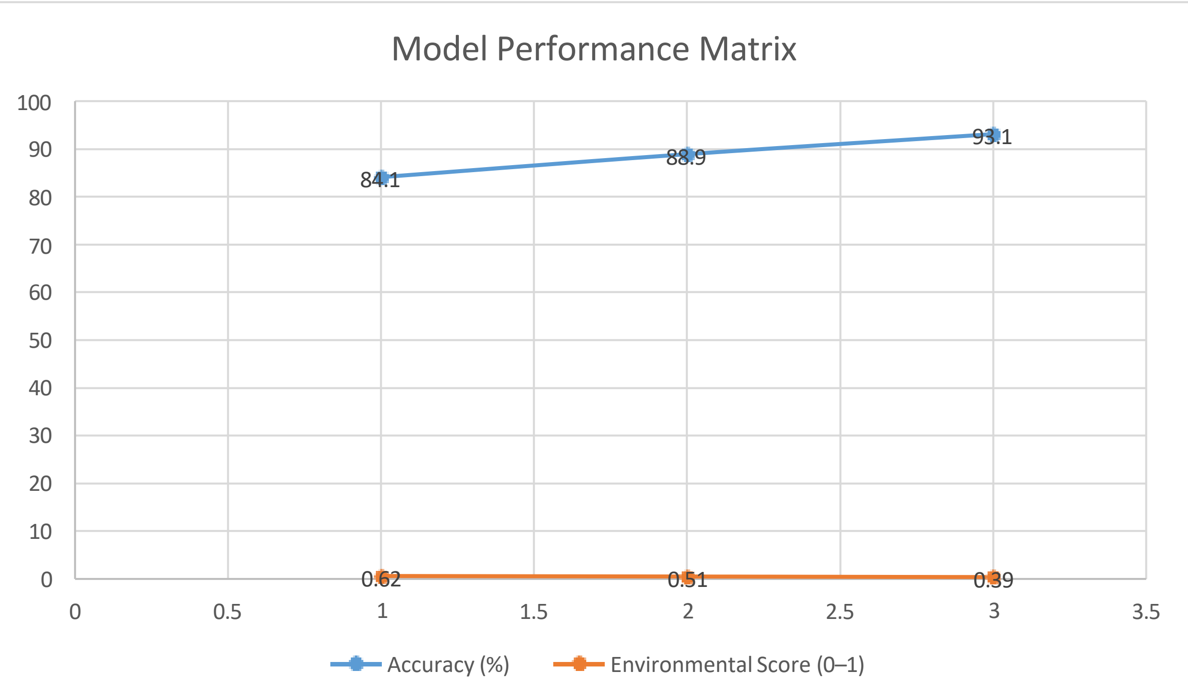

FIGURE 4: MODEL PERFORMANCE MATRIX

In figure 4, the hybrid model is clearly located in the best quadrant, top-left, high accuracy, and low environmental cost whereas the other models are located in secondary quadrants. This strengthens the argument that the suggested methodology is not just a technical enhancement but a game-changer in the medical decision intelligences, which is part of green healthcare.The deployment issues were also discussed, notably the system transparently. Although deep learning models might be accurate, they are not always explainable. This shortcoming was overcome by the fuzzy logic element, which provides rule-based determinations that may be examined and modified by clinicians. These rules of thumb could also be customized to regional environmental limits, or hospital-specific sustainability targets [9].

V. CONCLUSION

Fuzzy logic and AI in medical data analysis create a potent framework of opportunities to develop the quality of healthcare and environmental sustainability. The proposed system can support eco-conscious clinical decisions because it will manage uncertainty and increase predictive capacity. Such a twofold advantage renders the method especially topical in the era of climate emergency and data-medicine. The next direction of research can be real-time connectivity with hospital systems and adoption at the policy level towards green healthcare.

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