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Precision Pediatric Neurology: Leveraging Artificial Neural Networks for Accurate Diagnosis of Neurological Disorders in Children

Gita Kirani[1], Adiratna[2], Chintya Hastanti[3]
[1,2,3]Department of Engineering and Informatics, Gajayana University, Indonesian, Jl. Mertojoyo Blok L, Merjosari, Kec. Lowokwaru, Malang City, East Java 65144

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ABSTRACT

This research delves into the development and implications of an expert system leveraging artificial neural networks (ANNs) for diagnosing neurological disorders in pediatric patients. By amalgamating the intricacies of pediatric neurology with cutting-edge AI technology, this study endeavors to enhance diagnostic accuracy, facilitate timely interventions, and personalize treatment strategies for children grappling with neurological conditions. The research elucidates the architectural framework, data processing methodologies, and training techniques employed in constructing the expert system. The integration of diverse neurological data sources, including EEG readings, MRI scans, and patient histories, underpins the system's capability to discern patterns and generate accurate diagnoses. Ethical considerations loom prominently throughout this exploration, emphasizing the paramount importance of patient data privacy, informed consent, transparency in AI decision-making, and the collaborative role of AI alongside healthcare providers. The study culminates in unveiling the practical implications of implementing such an expert system in real clinical settings. Usability, reliability, regulatory compliance, and the intricate dynamics of human-AI interaction in healthcare emerge as critical pillars in the successful integration of AI-driven diagnostic tools.

Corresponding Author:

Gita Kirani,
Department of Engineering and Informatics,
Gajayana University,
Jl. Mertojoyo Blok L, Merjosari, Kec. Lowokwaru, Malang City, East Java 65144.
Email: gitakirani@unigamalang.ac.id

1. INTRODUCTION

Neurological disorders in children represent a diverse spectrum of conditions that affect the nervous system's structure, function, or both(Fung et al., 2017). These disorders encompass a wide range of conditions, including epilepsy, autism spectrum disorders, cerebral palsy, ADHD (Attention-Deficit/Hyperactivity Disorder), developmental delays, and more. Their prevalence is significant, impacting millions of children worldwide, and their effects reverberate profoundly in the lives of affected individuals and their families.

The prevalence of these disorders is staggering, with statistics indicating that up to 15% of children worldwide experience one or more neurological disorders(Olness, 2003). These conditions can manifest in various ways, impacting cognitive, motor, behavioral, and social development. Their

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effects can be lifelong, shaping the individual's trajectory, influencing their ability to learn, communicate, and interact with the world around them.

The impact of neurological disorders on children is multifaceted and profound(Trogrlić et al., 2019). Physically, these disorders might present challenges in mobility, coordination, or muscle control. Cognitively, they can hinder learning, memory, attention, and problem-solving abilities. Behaviorally, they might manifest as difficulties in social interaction, emotional regulation, or impulse control. The combination of these challenges often places significant stress on families and caregivers, impacting their daily lives and altering family dynamics(Sales, 2003).

Early and accurate diagnosis of neurological disorders in children is of paramount importance(Novak et al., 2017). Timely identification of these conditions allows for early interventions, therapies, and specialized support tailored to the child's specific needs. Early interventions can significantly improve outcomes, potentially mitigating the severity of symptoms, enhancing developmental progress, and empowering children to better navigate their world. Furthermore, accurate diagnosis aids in appropriate treatment planning, facilitating access to the right therapies and support services.

However, diagnosing neurological disorders in children is complex. Symptoms may overlap or evolve over time, making precise identification challenging(Rutter, 2011). Moreover, access to specialized healthcare professionals proficient in diagnosing these conditions might be limited, particularly in underserved areas or regions lacking resources.

This underscores the critical need for innovative solutions in pediatric neurology(Wainwright et al., 2016). Advancements in technology, particularly in the realm of artificial intelligence and machine learning, offer promising avenues. Developing expert systems using artificial neural networks holds potential in revolutionizing the diagnostic process(Wei et al., 1998). These systems can sift through vast amounts of clinical data, recognize intricate patterns, and aid healthcare professionals in making more accurate and timely diagnoses.

Recent advancements in artificial intelligence, particularly in machine learning and neural networks, have demonstrated significant potential in medical applications, including disease diagnosis and prognosis(Huang et al., 2020). AI-based systems, such as expert systems and neural networks, can analyze complex data patterns, aiding healthcare professionals in making accurate and timely diagnoses.

Expert systems are AI-driven computer programs designed to emulate human expertise in a specific domain(Sarker et al., 2021). They operate on a knowledge base, a repository of structured information derived from expert human knowledge, rules, and heuristics. These systems employ inference engines that use reasoning and decision-making algorithms to process inputs and generate recommendations, diagnoses, or solutions.

In medical contexts, expert systems excel in leveraging accumulated medical knowledge and diagnostic guidelines(Mciver et al., 2013). They incorporate vast amounts of data, including symptoms, patient history, and medical literature, to aid healthcare professionals in making informed decisions. Expert systems in medical diagnosis act as invaluable decision support tools, assisting clinicians in narrowing down potential diagnoses based on presented symptoms and patient data(Musen et al., 2021).

ANNs are a subset of machine learning models inspired by the structure and functionality of the human brain's neural networks(Shanmuganathan, 2016). Comprising interconnected nodes (neurons) organized into layers, ANNs process information through these interconnected nodes, where each node performs simple computations and passes the output to subsequent layers. Through a process called training, ANNs learn patterns and relationships within datasets, enabling them to make predictions or classifications without explicit programming(Abiodun et al., 2019).

In medical diagnosis, ANNs showcase remarkable capabilities(Lee et al., 2017). They can analyze complex, multidimensional medical data, such as imaging scans, genetic information, or patient records, to recognize intricate patterns that might elude human perception. ANNs learn from labeled datasets, extracting features and discerning correlations that aid in disease identification, prognosis, and treatment planning.

Both expert systems and ANNs find extensive applications in medical diagnosis(Wang et al., 2000). Expert systems assist clinicians by providing decision support, utilizing established medical guidelines and rules to suggest potential diagnoses based on presented symptoms and patient data. These systems enhance diagnostic accuracy by amalgamating vast medical knowledge into actionable insights.

ANNs, on the other hand, excel in pattern recognition and data analysis. They analyze diverse medical datasets, including MRI images, genomic data, and patient histories, to identify subtle patterns indicative of diseases(Myszczynska et al., 2020). ANNs contribute to diagnostic accuracy by learning from data, assisting in early detection, prognosis, and personalized treatment planning.

The integration of expert systems and ANNs holds immense promise in augmenting healthcare professionals' capabilities(Ahmed et al., 2020). Combining the structured knowledge representation of expert systems with the pattern recognition prowess of ANNs can potentially create more robust, accurate, and efficient diagnostic tools. Such synergies enable comprehensive analysis and interpretation of medical data, fostering improved patient outcomes and advancing the landscape of medical diagnosis.

The research aims to leverage the capabilities of AI, specifically expert systems utilizing artificial neural networks, to create a robust and accurate diagnostic tool for neurological disorders in children. By harnessing the power of machine learning and medical expertise, the goal is to develop a system that can assist healthcare professionals in diagnosing these disorders more efficiently and accurately.

2. RESEARCH METHOD

The methodology employed in the research of developing an "Expert System for Diagnosing Neurological Disorders in Children Using Artificial Neural Networks" encompasses a structured and systematic approach aimed at creating a robust diagnostic tool. This methodological framework integrates several key steps crucial for the successful development and evaluation of the expert system.

The research begins by clearly defining the problem diagnosing neurological disorders in children and delineating the scope of the study(Masten et al., 1990). This involves specifying the targeted disorders, data sources (such as EEG, MRI scans, patient histories), and the intended outcomes of the expert system.

Diverse neurological data, including EEG readings, MRI scans, patient histories, and potentially genetic information, is collected(Myszczynska et al., 2020). This involves obtaining consent, accessing relevant databases, or collaborating with medical institutions. Data preprocessing techniques, like cleaning, normalization, feature engineering, and handling missing values, are applied to ensure data quality and readiness for analysis.

Feature selection methods are employed to identify the most informative and relevant attributes from the collected data(Chandrashekar & Sahin, 2014). Techniques such as statistical tests, feature importance ranking, or dimensionality reduction aid in selecting the key features that contribute significantly to the diagnosis of neurological disorders. The data is then represented in a structured format suitable for input into the artificial neural network.

The neural network architecture is meticulously designed, considering factors such as the number of layers, types of neurons, activation functions, and network topology(Basheer & Hajmeer, 2000). Architectural decisions aim to optimize the network's ability to learn complex patterns and make accurate diagnoses based on the extracted features from neurological data.

The prepared data is split into training, validation, and test sets(Tropsha et al., 2003). The artificial neural network undergoes training using the training dataset, where iterative optimization techniques, such as backpropagation, adjust network parameters to minimize errors. Cross-validation techniques, hyperparameter tuning, and regularization methods are employed to enhance model performance, prevent overfitting, and ensure generalizability.

Established medical guidelines, diagnostic criteria, and domain-specific rules are integrated into the expert system(Mekruksavanich, 2016). This expert knowledge enhances the system's decision-making process, aligning it with clinical expertise and ensuring that the system's outputs are in line with established medical practices.

The developed expert system undergoes rigorous evaluation using various performance metrics, including accuracy, sensitivity, specificity, precision, and area under the curve (AUC)(Tiwari

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et al., 2022). The system's diagnostic performance is assessed against a separate test dataset or through cross-validation techniques to validate its accuracy and reliability.

The system undergoes iterative refinement based on feedback from clinical validation, new data incorporation, and further model enhancements(Cockrell & An, 2021). Continuous learning and updates ensure the system's adaptability, relevance, and accuracy in diagnosing neurological disorders in children.

A mathematical formulation for an artificial neural network (ANN) used in diagnosing neurological disorders involves defining the architecture, operations, and parameters of the model.

a. Let's consider a neural network with L layers:
   - Input layer (Layer 0) with n features: $X = [x_{1,}\ x_{2,}\ldots,x_n]$
   - Hidden layers (Layer 1 to Layer L-1 with $m_{1,}\ldots,m_{L-1}$ neurons respectively
   - Output layer (Layer L) with p output neurons representing possible neurological disorder classes

Each neuron in the hidden and output layers uses an activation function *f* (commonly ReLU, Sigmoid, or Tanh) and has associated weights *W* and biases *b*.

b. The mathematical representation of the network can be expressed as follows:
   - For each hidden layer *l* = 1,2,…L-1:
     $Z^{(l)} = W^{(l)}.\ A^{(l-1)} + b^{(l)}$
     $A^{(l)} = \mathrm{f}(Z^{(l)})$
     where:
     - $Z^{(l)}$ is the pre-activation value in layer *l*
     - $A^{(l)}$ is the pre-activation value in layer *l*
     - $W^{(l)}$ is the weight matrix for layer *l*
     - $b^{(l)}$ is the bias vector for layer *l*
     - $A^{(0)}$ *X* is the input data
   - For the output layer L:
     $Z^{(L)} = W^{(L)}.\ A^{(L-1)}+b^{(l)}$
     $\hat{Y} = \mathrm{Softmax}\ (Z^{(L)})$
     Loss = Cross-entropy loss $(\hat{Y},Y_{true})$
     where:
     - $\hat{Y}$ is the predicted output probabilities for each class
     - Y_{true} is the true label or diagnosis (one-hot encoded for multiclass classification)
     - Softmax is the activation function for multiclass classification
     - Cross-entropy loss measures the difference between predicted and true class probabilities

3. RESULTS AND DISCUSSIONS

3.1 Result

A numerical illustrating a simplified neural network used for diagnosing neurological disorders in children.

a. Neural Network Architecture:
   - Input layer (Layer 0): 2 features from EEG data
   - Hidden layer (Layer 1): 3 neurons
   - Output layer (Layer 2): 2 neurons representing two neurological disorder classes

b. Initialization:
   For simplicity, let's assume initial weights ($W^{(1)}$ and $W^{(2)}$) and biases ($b^{(1)}$ and $b^{(2)}$) are initialized randomly.

b. Data Input:
   Suppose we have a single data point:
   EEG features: X = [0.6-1.2] (two EEG readings)

c. Forward Propagation:
   - Initialize weights and biases randomly.
   - Calculate activations for hidden layer:

$Z^{(1)} = W^{(1)}.\mathrm{X} + b^{(l)}$

Assume:

$$W^{(1)} = \begin{bmatrix} 0.1 & 0.4 \\ -0.3 & 0.5 \\ 0.8 & -0.2 \end{bmatrix}$$

$$b^{(1)} = \begin{bmatrix} 0.2 \\ -0.4 \\ 0.1 \end{bmatrix}$$

$A^{(1)}$ = ReLU ($Z^{(1)}$) (ReLU activation function)

- Calculate aktivaton for output layer:

  $Z^{(2)} = W^{(2)}.A^{(1)} + b^{(2)}$

  Assume:

  $$W^{(2)} = \begin{bmatrix} -0.5 & 0.3 & 0.7 \\ 0.2 & -0.1 & 0.9 \end{bmatrix}$$

  $$b^{(2)} = \begin{bmatrix} -0.3 \\ 0.5 \end{bmatrix}$$

  $\hat{Y}$ = Softmax ($Z^{(2)}$) (Softmax activation function)

d. Prediction:
   Given the calculated $\hat{Y}$, the predicted probabilities for each class would be obtained through the Softmax function.

e. Training and Loss Calculation:
   The network would be trained with labeled data using backpropagation to minimize the cross-entropy loss function.

The forward propagation process generated predicted probabilities for the two neurological disorder classes based on the EEG features provided. These predicted probabilities ($\hat{Y}$) represent the model's estimation of the likelihood of the sample belonging to each class.

For instance, let's assume the predicted probabilities are $\hat{Y}$= [0.6, 0.4] his implies that, according to the hypothetical neural network model, the input EEG features are more likely associated with the first neurological disorder class (60% probability) compared to the second class (40% probability).

3.1.1 A Programming Algorithm

Here's a simplified Python pseudocode algorithm representing the forward propagation process of a basic neural network for diagnosing neurological disorders based on the mathematical formulation discussed earlier.

```
# Neural Network Initialization
# Assuming random initialization of weights and biases
initialize_weights_and_biases()

# Input Data
X = [0.6, -1.2]  # EEG features

# Forward Propagation
# Hidden Layer
Z1 = W1 * X + b1  # Calculate pre-activation values for Layer 1
A1 = ReLU(Z1)     # Apply ReLU activation function for Layer 1

# Output Layer
Z2 = W2 * A1 + b2  # Calculate pre-activation values for Output Layer
Y_hat = Softmax(Z2)  # Apply Softmax activation function for multiclass classification

# Display Predicted Probabilities
print("Predicted Probabilities:", Y_hat)
```

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3.2 Discussion

3.2.1 The Practical Implications Of The System In Clinical Settings And Its Potential Impact On Diagnosing Neurological Disorders In Children

The introduction of an expert system utilizing artificial neural networks for diagnosing neurological disorders in children holds profound promise and practical implications within clinical settings, significantly impacting the landscape of pediatric neurology. One of the most significant practical implications lies in the system's potential to enhance diagnostic accuracy. By leveraging vast datasets and intricate pattern recognition capabilities, the system aids healthcare professionals in making more precise and timely diagnoses of neurological disorders in children. This accuracy can facilitate early intervention and tailored treatment plans, ultimately improving patient outcomes.

The system's ability to swiftly process diverse neurological data sources, including EEG readings, MRI scans, patient histories, and genetic information, expedites the diagnostic process. Early detection of neurological disorders enables prompt interventions and specialized care, potentially mitigating the progression of conditions and enhancing developmental outcomes in children.

Accurate diagnoses empower clinicians to devise personalized treatment strategies suited to each child's specific neurological condition. Tailored interventions, therapies, and support services can be initiated promptly, addressing the unique needs and challenges associated with different disorders. This personalized approach enhances the efficacy of treatments and improves the quality of life for affected children and their families.

The system's efficiency in analyzing complex neurological data streamlines the diagnostic process, potentially reducing healthcare burdens. It optimizes resource allocation, allowing healthcare professionals to focus on interpretation, decision-making, and patient care rather than solely on data analysis. This efficiency can contribute to more streamlined and cost-effective healthcare delivery systems.

Moreover, the system's capacity for iterative learning and improvement presents an ongoing opportunity for advancement. Continuous updates, incorporating new data, clinical insights, and evolving medical knowledge, ensure the system remains up-to-date and adaptable to changing diagnostic criteria and advancements in pediatric neurology.

3.2.2 Practical Considerations For Implementing The Expert System In Real Clinical Settings, Including Usability, Reliability, And Regulatory Compliance

Implementing an expert system for diagnosing neurological disorders in children using artificial neural networks within real clinical settings requires careful consideration of several practical factors to ensure usability, reliability, and regulatory compliance. These considerations are pivotal for successful integration and effective utilization of the system within clinical practice.

Designing an intuitive and user-friendly interface is crucial for the system's adoption by healthcare professionals. The interface should facilitate seamless interaction, easy data input, and interpretation of diagnostic outputs. User-centered design principles, incorporating feedback from clinicians, ensure the system aligns with their workflow, making it more accessible and practical for daily use.

Ensuring the system's reliability and accuracy is fundamental. Rigorous validation, testing, and ongoing quality assurance protocols are essential to validate the system's diagnostic accuracy against established medical standards. Regular performance evaluations, including monitoring false positives, false negatives, and overall predictive capabilities, help maintain reliability and instill confidence among healthcare providers.

The system should provide transparent and interpretable outputs. Healthcare professionals must comprehend and trust the system's diagnostic decisions. Mechanisms for explaining the rationale behind diagnoses, such as highlighting relevant features or providing reasoning for predictions, enhance trust and usability.

Maintaining high data quality, integrity, and security is paramount. Compliance with data protection regulations, including HIPAA (Health Insurance Portability and Accountability Act) or

GDPR (General Data Protection Regulation), safeguards patient privacy and confidentiality. Additionally, ensuring data quality through proper collection, storage, and encryption mechanisms is essential for accurate diagnoses and ethical considerations.

Adherence to regulatory standards and medical guidelines is crucial. Compliance with regulatory frameworks, such as FDA (Food and Drug Administration) or CE (Conformité Européenne) marking, ensures the system meets safety, efficacy, and quality standards before deployment in clinical settings. Aligning with medical guidelines and ethical codes ensures ethical and responsible use of the system.

Provision of comprehensive training programs for healthcare professionals facilitates effective utilization of the system. Ongoing technical support, regular updates, and continuous learning opportunities regarding system enhancements, new diagnostic insights, or changes in medical guidelines aid in the system's continuous improvement and adaptation to evolving clinical needs.

3.2.3 Consideration Of Ethical Implications Regarding The Use Of AI In Medical Diagnosis

The integration of Artificial Intelligence (AI) in medical diagnosis, including its application in expert systems for diagnosing neurological disorders in children, raises profound ethical considerations that extend beyond the realm of technological advancements. These ethical implications encompass various facets, from data privacy and informed consent to the intricate dynamics of human-AI interaction in healthcare settings.

The utilization of AI in medical diagnosis relies heavily on vast amounts of sensitive patient data, including EEG readings, MRI scans, genetic information, and patient histories. Ensuring robust data privacy measures is crucial to safeguard patient confidentiality and prevent unauthorized access or misuse of sensitive health information. Ethical AI deployment mandates adherence to stringent data protection regulations (e.g., HIPAA, GDPR) to uphold patient privacy rights.

Maintaining transparency and ensuring informed consent from patients regarding the use of their data in AI-driven diagnostic systems are imperative ethical considerations. Patients must understand how their data will be utilized, the implications of AI-driven diagnoses, and have the autonomy to consent or opt-out of data utilization for such purposes. Clear communication and transparency in explaining the role of AI in clinical decision-making foster trust between patients, healthcare providers, and the technology.

The opacity of AI algorithms poses challenges in interpreting and explaining their decisions, especially in complex medical diagnoses. Ensuring the explainability of AI-generated diagnoses is crucial to build trust among healthcare professionals and patients. Efforts to develop transparent AI models that provide understandable justifications for diagnoses are essential for ethical AI integration in healthcare.

The interaction between AI systems and healthcare professionals in clinical settings introduces ethical considerations regarding the division of responsibilities and decision-making authority. AI systems should augment, not replace, human expertise, emphasizing a collaborative approach where AI serves as a decision support tool. Healthcare providers remain accountable for interpreting AI-generated results and incorporating them into comprehensive patient care plans.

Guarding against biases present in datasets used to train AI models is critical to prevent algorithmic biases in diagnoses, especially considering diverse patient populations. Ethical AI development necessitates mitigating biases and ensuring fairness in diagnoses across different demographic groups, avoiding perpetuation of healthcare disparities.

Continuous evaluation, monitoring, and ethical scrutiny of AI systems in healthcare are imperative. Establishing regulatory frameworks that govern the development, deployment, and monitoring of AI systems in medical diagnosis ensures adherence to ethical principles, safety, effectiveness, and accountability.

4. CONCLUSION

In the evolution of medical technology, the development of an expert system utilizing artificial neural networks for diagnosing neurological disorders in children represents a remarkable stride towards precision and personalized healthcare. This research journey has traversed the convergence of cutting-edge technology and the intricacies of pediatric neurology, unveiling promising prospects alongside critical ethical considerations. The culmination of this research underscores the potential

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for transformative change in pediatric neurology. The integration of artificial neural networks harnesses the power of machine learning to process intricate neurological data, offering the prospect of more accurate and timely diagnoses. This advancement holds the key to early interventions, tailored treatments, and improved prognoses for children grappling with neurological disorders. Central to this pursuit of innovation are the ethical imperatives ingrained in the ethical compass of AI-driven healthcare. Upholding patient data privacy, transparency in AI decision-making, ensuring informed consent, and guarding against biases are fundamental tenets. This ethical underpinning not only safeguards patient rights but also fortifies trust between technology, healthcare providers, and the patients they serve. Crucially, the symbiotic relationship between human expertise and AI capabilities emerges as a guiding principle. The expert system, designed to augment clinical decision-making rather than supplant it, heralds a paradigm where AI serves as a powerful ally, empowering healthcare providers with enhanced diagnostic precision and comprehensive insights. In the denouement of this research, the fusion of artificial intelligence and pediatric neurology brings to fruition a promising vista of precision healthcare. The strides made underscore not only the technological prowess but also the ethical responsibility ingrained in harnessing AI for the betterment of children's health. In this union of innovation and ethics, lies the potential to revolutionize pediatric neurological care, illuminating a path towards a future where precision, empathy, and ethical integrity harmoniously converge for the well-being of our children.

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