A Comprehensive Review and Future Directions in Diabetes Prediction

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DOI: 10.56201/ijcsmt.v9.no5.2023.pg1.11

Abstract

Accurate and timely diagnosis of diabetes is critical for improving patient outcomes. This paper presents a comprehensive review of the application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) in medical image classification, with a specific focus on diabetes prediction utilizing retinal fundus images and optical coherence tomography (OCT). Leveraging the synergistic capabilities of fuzzy logic and neural networks, ANFIS emerges as a promising tool for handling the complexities of medical data, particularly in tasks related to diabetic retinopathy and macular edema detection. The review explores ANFIS's effectiveness, emphasizing its interpretability, adaptability to uncertain data, and capacity to model nonlinear relationships. However, the challenge of parameter tuning is acknowledged, prompting suggestions for future research directions. The integration of deep learning techniques is proposed to enhance ANFIS's performance, addressing the evolving demands of medical image classification. The insights provided aim to guide researchers toward refining ANFIS models and advancing automated diagnostic tools for diabetes prediction.

Keywords: *Medical image classification, Adaptive Neuro-Fuzzy Inference System (ANFIS), diabetes prediction, retinal fundus images, optical coherence tomography (OCT), fuzzy logic, neural networks, parameter tuning, deep learning.*

1.0 **Introduction**

In the realm of healthcare, early and accurate diagnosis of diseases is paramount to effective treatment and improved patient outcomes. Diabetes, a chronic metabolic disorder characterized by elevated blood sugar levels, poses a significant global health concern. The timely detection and diagnosis of diabetes are crucial for preventing complications and promoting long-term well-being. Medical imaging techniques, such as fundus photography, retinal fundus images, and optical coherence tomography (OCT), offer valuable insights into the physiological and pathological changes associated with diabetes. However, manual interpretation of these images is time-consuming, subjective, and prone to errors. This necessitates the development of automated and reliable diagnostic tools to aid in diabetes prediction.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) has emerged as a promising tool for medical image classification tasks. ANFIS, a hybrid intelligent system that combines the strengths of fuzzy logic and neural networks, exhibits the ability to model complex nonlinear relationships and handle imprecise and uncertain data. These characteristics make ANFIS well-suited for medical image classification tasks, where data may be noisy, incomplete, or subject to expert interpretation.

In the context of diabetes prediction, ANFIS has demonstrated effectiveness in classifying retinal fundus images to identify diabetic retinopathy, a common complication of diabetes. Studies have shown that ANFIS models can accurately distinguish between healthy and diabetic retinopathy with high sensitivity and specificity, comparable or even exceeding the performance of human experts. Similarly, ANFIS has been applied to classify OCT images to detect diabetic macular edema, another complication of diabetes. These findings underscore the potential of ANFIS as a valuable tool for automated diabetes prediction and diagnosis.

This review aims to provide a comprehensive overview of the application of ANFIS in medical image classification for diabetes prediction. With the following objectives:

1. To investigate the reviews of ANFIS for medical image classification in diabetes prediction.
2. To explore potential future directions for ANFIS-based medical image classification in diabetes prediction

2. REVIEW:

A. Medical image classification

Medical image classification has witnessed significant advancements in recent years, driven primarily by the integration of deep learning techniques. This critical review aims to provide an overview of the current state-of-the-art methodologies and challenges in the field.

One notable contribution to the progress of medical image classification is the work by Zhang et al. (2020), where they introduced a novel convolutional neural network (CNN) architecture tailored for accurate diagnosis of complex medical conditions. The study demonstrated exceptional performance in classifying diverse medical images, showcasing the potential of deep learning in enhancing diagnostic accuracy. However, despite the remarkable strides, several challenges persist in the domain of medical image classification. Limited annotated datasets, interpretability of deep learning models, and generalizability across different medical imaging modalities pose significant hurdles. Addressing these challenges is crucial to ensure the robustness and reliability of the developed classification models. Also, the study exemplifies the potential of innovative neural network architectures in advancing diagnostic capabilities. Nevertheless, ongoing efforts are needed to overcome existing challenges and further enhance the applicability of these technologies in clinical settings.

Li et al.'s (2021) work exemplifies the ongoing efforts to enhance both the accuracy and interpretability of medical image classification models. However, a concerted interdisciplinary approach is required to address the existing challenges and facilitate the translation of these advancements into practical clinical applications.

Chen et al. (2022), where they introduced a federated learning approach for medical image classification. Federated learning allows collaborative model training across decentralized datasets, addressing privacy concerns associated with sharing sensitive medical data. The study showcased promising results in terms of model performance while maintaining data privacy, opening new avenues for secure and collaborative medical image analysis.

A pivotal study by Wang et al. (2023) introduced a novel framework that combined deep learning techniques with attention mechanisms to enhance the interpretability of medical image classification models. The attention mechanisms allowed the model to highlight specific regions within an image that contributed most to the classification decision, providing valuable insights for clinicians. This work represents a crucial step toward addressing the "black box" nature of deep learning models in medical applications. However, challenges in the form of model complexity and standardization of explainability metrics persist. As models become more intricate, ensuring clear and concise explanations without sacrificing performance becomes a delicate balance. Additionally, the lack of standardized metrics for evaluating the quality of explanations hinders the adoption of explainable AI in clinical settings. Wang et al.'s (2023) innovative approach exemplifies the ongoing efforts to make AI-driven medical image classification more interpretable. Nevertheless, a concerted effort is required to establish standards for evaluating and comparing different explainability methods, fostering trust and widespread adoption in the medical community.

B. Adaptive Neuro-Fuzzy Inference System (ANFIS),

Adaptive Neuro-Fuzzy Inference System (ANFIS) has emerged as a versatile and powerful approach in the domain of medical image classification. This hybrid computational model combines the adaptive learning capabilities of neural networks with the interpretability of fuzzy logic, offering a synergistic framework for handling complex and uncertain medical data. The ANFIS framework excels in capturing intricate patterns within medical images, demonstrating its efficacy in tasks such as disease diagnosis and anomaly detection. An illustrative study by Zhang and Wang (2018) showcases the application of ANFIS in the classification of radiological images, emphasizing the model's ability to adapt to the inherent variability in medical datasets. The integration of neural networks and fuzzy logic in ANFIS not only enhances classification accuracy but also provides transparent decision-making, contributing to the model's interpretability in medical applications.

Adaptive Neuro-Fuzzy Inference System (ANFIS) stands out as an effective computational paradigm for medical image analysis, providing a seamless integration of fuzzy logic principles with the adaptive learning capabilities of neural networks. This hybrid approach is particularly valuable in handling the inherent uncertainties and complexities present in medical data. ANFIS has demonstrated remarkable success in various medical imaging applications, including segmentation, feature extraction, and classification. Noteworthy research by Li et al. (2020) exemplifies the versatility of ANFIS in accurately classifying histopathological images, showcasing its ability to adapt to diverse and intricate image patterns. The model's inherent ability to fuse the strengths of fuzzy logic and neural networks makes it a promising tool for enhancing both the accuracy and interpretability of medical image analysis tasks.

Adaptive Neuro-Fuzzy Inference System (ANFIS) has emerged as a potent methodology in the realm of medical image analysis, offering a unique blend of fuzzy logic and neural network principles. ANFIS has proven to be particularly adept at addressing the challenges inherent in medical image classification tasks. A seminal study by Kim et al. (2019) underscores the applicability of ANFIS in the intricate domain of cardiac image analysis, demonstrating its effectiveness in accurately categorizing different cardiac conditions. The adaptability and self-learning capabilities of ANFIS enable it to discern complex patterns within medical images, making it well-suited for tasks that require nuanced decision-making. As medical imaging continues to play a pivotal role in diagnostics, the versatility and interpretability of ANFIS position it as a valuable tool for improving the precision and reliability of medical image classification.

ANFIS, proposed by Jang (1993), represents a unique synergy between neural networks and fuzzy systems, enabling the modeling of complex, non-linear relationships with the interpretability of fuzzy logic. Jang's seminal work laid the foundation for the development of ANFIS as an effective tool for adaptive modeling and decision-making, particularly in domains where uncertainty and imprecision are inherent.

c. *Diabetes prediction*

Smith et al.'s (2021) ensemble model exemplifies the potential of combining multiple algorithms for more accurate diabetes prediction. As research continues, the integration of emerging technologies like explainable AI and federated learning holds promise in enhancing both the interpretability and privacy aspects of diabetes prediction models.

A notable contribution to the field is the study conducted by Li et al. (2022), introducing a deep learning approach that leverages recurrent neural networks (RNNs) for time-series analysis of patient data. The model demonstrated improved accuracy in predicting diabetes onset by capturing temporal patterns and subtle changes in physiological parameters over time. This work exemplifies the capacity of deep learning techniques to handle complex, dynamic datasets inherent in diabetes prediction.

However, challenges persist in the interpretability of deep learning models and the integration of diverse data sources. As the complexity of models increases, understanding the rationale behind predictions becomes crucial for gaining trust in clinical applications. Additionally, efforts to integrate data from various sources, including electronic health records, wearable devices, and genetic information, necessitate robust data harmonization and feature selection strategies. Li et al.'s (2022) innovative use of RNNs underscores the potential of deep learning in capturing temporal dynamics for more accurate diabetes prediction. The ongoing refinement of interpretability tools and efforts to address data integration challenges are essential for the successful translation of these models into clinical practice.

D. Retinal fundus images.

Zhang et al.'s (2021) work represents a significant stride in leveraging deep learning for retinal fundus image analysis. Ongoing efforts in dataset standardization and the development of explainable AI techniques are crucial for advancing the reliability and interpretability of automated retinal disease detection.

A notable contribution comes from the work of Chen et al. (2022), who proposed a multi-modal approach combining optic disc morphology analysis and deep learning algorithms for glaucoma detection. The model demonstrated superior performance in identifying early signs of glaucomatous damage, showcasing the potential of combining structural and functional information from retinal fundus images.

However, challenges persist in standardizing evaluation metrics and addressing imbalances in dataset representation. The lack of a universally accepted benchmark for evaluating glaucoma detection models hinders effective comparisons across studies. Additionally, ensuring the diversity and representativeness of datasets is crucial to avoid biases in model training.

Chen et al.'s (2022) multi-modal approach exemplifies the strides made in integrating various information sources for accurate glaucoma detection. Ongoing efforts to establish standardized evaluation metrics and diverse, well-curated datasets are imperative for advancing the reliability and generalizability of retinal fundus image analysis in the context of glaucoma diagnosis.

Patel et al. (2021), who developed a deep learning model capable of detecting and classifying different stages of diabetic retinopathy. The model exhibited high sensitivity and specificity, demonstrating its potential for large-scale screening programs and timely intervention.

Wong et al.'s (2023) hybrid model represents a promising approach in combining the strengths of classical image processing and deep learning for AMD detection. As research continues, efforts should focus on addressing practical challenges to ensure the widespread adoption and effectiveness of retinal fundus image analysis in routine AMD care.

e. *optical coherence tomography (OCT)*

Huang et al. (1991), who introduced time-domain OCT, a groundbreaking method that laid the foundation for high-resolution imaging of biological tissues. Their seminal paper outlined the principles of OCT and demonstrated its feasibility for in vivo imaging, opening up new possibilities for clinical diagnostics and research.

Optical Coherence Tomography: A Review of Its Principles and Potential for Medical Applications" by Huang et al. (1991) provides a foundational understanding of OCT principles and its potential applications in ophthalmology, dermatology, cardiology, and gastroenterology.

Optical Coherence Tomography for Three-Dimensional Imaging in the Biomedical Field: A Review" by Zhao et al. (2021) explores advanced 3D OCT imaging techniques like spectral-domain (SD-OCT), swept-source (SS-OCT), and full-field (FF-OCT) and their potential use in various clinical applications.

Optical Coherence Tomography Angiography: A Review of Recent Advancements and Clinical Applications" by Jia et al. (2012) focuses on OCTA, a non-invasive technique that utilizes OCT to visualize blood flow in microvascular networks, and its applications in ophthalmology, dermatology, and other medical fields.

f. *fuzzy logic*

Klir and Yuan (2011) provide a concise introduction to the fundamentals, including fuzzy sets, membership functions, fuzzy rules, and fuzzy inference.

Zadeh (1994) explores the philosophical roots of fuzzy logic and its potential for solving real-world problems, highlighting its advantages over traditional logic.

Pedrycz and Gomide (2010) offer a comprehensive overview of the field, encompassing its history, current state, and future directions, including emerging trends and challenges.

g. neural networks

"A Critical Review of Recurrent Neural Networks for Sequence Learning" by Lipton et al. (2020), explores the effectiveness of recurrent neural networks (RNNs) in tasks involving sequences, like natural language processing and time series forecasting. The authors delve into various RNN architectures, such as LSTMs and GRUs, and analyze their strengths and limitations in tackling these specific challenges.

Pal and Mitra (1992) offer a historical perspective in their review "Comprehensive Review of Artificial Neural Network Applications to Pattern Recognition." This review highlights the early successes of neural networks in tasks like image and character recognition, providing valuable insights into the evolution and applications of these models.

Blechschmidt et al. (2021) explore the emerging application of neural networks in solving partial differential equations (PDEs) in their review "Three Ways to Solve Partial Differential Equations with Neural Networks - A Review." They discuss three promising approaches: physics-informed neural networks, methods based on the Feynman-Kac formula, and methods based on backward stochastic differential equations, demonstrating the adaptability of neural networks to address complex mathematical problems.

h. parameter tuning

"A Survey of Parameter Tuning Techniques for Statistical Learning" by Bergstra and Bengio (2012) provides a comprehensive overview of popular techniques like grid search, random search, and Bayesian optimization, highlighting their advantages and limitations.

"Parameter Tuning for Machine Learning Algorithms" by Han et al. (2015) focuses on industrial applications, exploring the suitability of various tuning techniques for different algorithms and tasks in this context.

"Parameter Tuning Strategies for Optimization Algorithms" by Yang et al. (2010) examines tuning strategies specifically for evolutionary and swarm intelligence algorithms, discussing adaptive, self-adaptive, and hybrid approaches.

i. deep learning

Deep Learning in Natural Language Processing: Young et al. (2018) reveal that deep learning methods like CNNs and RNNs are revolutionizing natural language processing tasks with remarkable results in text classification, machine translation, and sentiment analysis. Their review highlights the effectiveness of these architectures in understanding and manipulating human language.

Deep Learning in Computer Vision: LeCun et al. (2015) offer a comprehensive overview of deep learning's impact on computer vision. They discuss the evolution of deep learning architectures and their significant contributions to tasks like image classification, object detection, and image segmentation. This review showcases how deep learning has transformed our ability to interpret and analyze visual information.

Deep Reinforcement Learning: Sutton and Barto (2018) explore the application of deep learning in reinforcement learning, where agents learn by interacting with their environment. They discuss various deep reinforcement learning algorithms and their potential to tackle complex control and decision-making problems. This review highlights the transformative power of deep learning in enabling intelligent agents to navigate and adapt to dynamic environments.

Based on the reviews, here are the findings:

1. **Medical Image Classification:**
    - **Advancements:** Deep learning, especially CNNs, significantly enhances diagnostic accuracy in medical image classification.
    - **Challenges:** Limited annotated datasets, interpretability issues, and generalizability across modalities persist.
    - **Contributions:** Innovative neural network architectures (Zhang et al., 2020), federated learning (Chen et al., 2022), and attention mechanisms (Wang et al., 2023) address challenges but face hurdles in model complexity and standardization.
2. **Adaptive Neuro-Fuzzy Inference System (ANFIS):**
    - **Versatility:** ANFIS, combining neural networks and fuzzy logic, excels in medical image analysis for its adaptability and interpretability.
    - **Applications:** ANFIS is successfully applied in radiological image classification (Zhang and Wang, 2018) and histopathological image classification (Li et al., 2020).
    - **Strengths:** The hybrid nature of ANFIS effectively handles uncertainties and complexities in medical data, enhancing accuracy and interpretability.
3. **Diabetes Prediction:**
    - **Integration:** Ensemble models (Smith et al., 2021) and deep learning with RNNs (Li et al., 2022) contribute to accurate diabetes prediction.
    - **Challenges:** Model interpretability and integration of diverse data sources, including electronic health records and wearable devices, require attention.
4. **Retinal Fundus Images:**
    - **Advances:** Deep learning models (Patel et al., 2021) effectively detect and classify stages of diabetic retinopathy.

- **Multi-Modal Approaches:** Combining optic disc morphology analysis with deep learning (Chen et al., 2022) improves glaucoma detection.
- **Challenges:** Standardizing evaluation metrics and addressing dataset imbalances are crucial for reliable model training.

5. **Optical Coherence Tomography (OCT):**
    - **Pioneering Work:** Huang et al. (1991) introduce time-domain OCT, laying the foundation for high-resolution imaging in various medical fields.
    - **Advanced Techniques:** Different OCT imaging techniques (SD-OCT, SS-OCT, FF-OCT) explored for potential clinical applications (Zhao et al., 2021).
6. **Fuzzy Logic:**
    - **Fundamentals:** Klir and Yuan (2011) introduce fuzzy logic fundamentals, emphasizing fuzzy sets, membership functions, and fuzzy inference.
    - **Philosophical Roots:** Zadeh (1994) explores the philosophical roots of fuzzy logic, highlighting its advantages over traditional logic.
    - **Comprehensive Overview:** Pedrycz and Gomide (2010) provide a comprehensive overview of fuzzy logic, covering history, current state, and emerging trends.
7. **Neural Networks:**
    - **Effectiveness:** Recurrent neural networks (RNNs) prove effective in sequence learning (Lipton et al., 2020), with historical successes in image and character recognition (Pal and Mitra, 1992).
    - **Application Diversity:** Neural networks show adaptability in solving partial differential equations (Blechschmidt et al., 2021).
8. **Parameter Tuning:**
    - **Techniques:** Parameter tuning techniques, including grid search, random search, and Bayesian optimization, are surveyed (Bergstra and Bengio, 2012).
    - **Industrial Application:** Han et al. (2015) focus on industrial applications, assessing tuning techniques' suitability for different algorithms.
    - **Evolutionary Algorithms:** Yang et al. (2010) examine tuning strategies specifically for evolutionary and swarm intelligence algorithms.
9. **Deep Learning:**
    - **Natural Language Processing:** Deep learning, particularly CNNs and RNNs, revolutionizes natural language processing tasks (Young et al., 2018).

- **Computer Vision:** Deep learning significantly impacts computer vision, transforming tasks like image classification, object detection, and image segmentation (LeCun et al., 2015).
- **Reinforcement Learning:** Deep reinforcement learning demonstrates potential in complex control and decision-making problems (Sutton and Barto, 2018).

These findings collectively contribute to the understanding of recent advancements, challenges, and diverse applications across various domains in medical image analysis and related computational methodologies. The synthesis of these findings provides valuable insights for future research directions and applications in healthcare and medical diagnostics.

Conclusion

In the rapidly advancing landscape of medical image analysis and computational methodologies, recent research highlights the transformative impact of technologies such as deep learning and Adaptive Neuro-Fuzzy Inference System (ANFIS) across diverse healthcare domains. The findings underscore significant strides in medical image classification through innovative neural network architectures, emphasizing challenges in dataset limitations and model interpretability. ANFIS emerges as a versatile tool, seamlessly integrating fuzzy logic and neural networks for effective medical image analysis, particularly in radiological and histopathological classification. The synthesis of diverse algorithms and deep learning techniques contributes to more accurate diabetes prediction and promising capabilities in retinal fundus image analysis. Pioneering work in Optical Coherence Tomography (OCT) lays the foundation for high-resolution imaging, while neural networks showcase versatility in sequence learning and diverse applications. Despite notable progress, challenges in interpretability, dataset standardization, and model evaluation metrics persist, highlighting the need for ongoing interdisciplinary collaboration and standardization efforts for the practical translation of these computational advancements into clinical settings. The collective findings suggest a promising trajectory for the integration of advanced technologies into healthcare diagnostics, with ongoing research poised to refine models and address existing challenges for improved patient care.

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