ISSN 2007-9737

Integrating Neural, Fuzzy, and Bio-Inspired Paradigms for Applications in Hypertension Modeling

Ivette Miramontes, Patricia Melin*

Tijuana Institute of Technology/TecNM,
Mexico

cynthia.miramontes@tectijuana.edu.mx, pmelin@tectijuana.mx

Abstract. This work proposes a hybrid neuro-fuzzy model to provide accurate and timely diagnosis of the risk of developing hypertension and cardiovascular events. It utilizes artificial neural networks, in both modular and monolithic forms, as well as fuzzy classifiers. Each component of the model has been optimized using various bio-inspired algorithms to maximize both the accuracy and robustness of the system. The proposed modules include blood pressure behavior analysis, classifiers for nocturnal blood pressure profiles, heart rate, blood pressure level and load, as well as assessment of the risk of developing hypertension and identification of cardiovascular events. The results indicate that risk predictions achieved accuracy rates of up to 100%. To optimize its clinical application, a graphical user interface, which we have named Soft Diagnosis, has been developed. This interface allows users to visualize historical data, behavioral trends, and comprehensive diagnoses in a clear and flexible manner. This study demonstrates that the integration of neural learning, fuzzy logic, and bio-inspired optimization constitutes a reliable and adaptable tool for the comprehensive assessment of cardiovascular risk.

Keywords. Optimization, bio-inspired algorithms, neural networks, fuzzy logic, hypertension.

1 Introduction

Hypertension is considered a major risk factor for the development of cardiovascular disease and is one of the leading causes of death worldwide. This condition presents silently and progressively, making timely detection and accurate risk assessment difficult during the initial stages [1–3]. For these reasons, there is a need to develop intelligent applications that support specialists in interpreting medical information and in the clinical decision-making process.

Significant progress in soft computing has been observed in recent years, facilitating the creation of models capable of handling ambiguous, imprecise, and nonlinear data-attributes intrinsic to medical systems.

Artificial neural networks, distinguished by their ability to learn and generalize effectively, are also crucial [4–8]. Another important technique for analysis is fuzzy logic, as it provides a representation that more accurately reflects human reasoning. Integrating both techniques facilitate the combination of machine learning with linguistic understanding, resulting in a hybrid approach of great relevance in the medical field [9–11].

However, the different neuro-fuzzy models currently available have certain limitations regarding their adaptability, parameter tuning, and effective implementation in clinical settings.

In this work, we propose a hybrid neuro-fuzzy model that combines neural networks with fuzzy logic, optimized using different bio-inspired algorithms, to address the problem. This method aims to provide a comprehensive assessment of the probability of developing hypertension and cardiovascular events over a period [12–15].

Our proposal includes incorporating neural modules, both modular and monolithic, as well as optimized fuzzy classifiers. These elements are integrated into a graphical user interface called Soft Diagnosis, designed for use by medical specialists in the field. The most significant contributions of our research can be summarized as follows:

ISSN 2007-9737

We present the design of a hybrid neuro-fuzzy model with a modular structure, capable of integrating diverse sources of patient information.

The system elements are optimized using bio-inspired algorithms, which improves diagnostic accuracy.

We develop a functional graphical user interface, adapted for expert users, which aims to facilitate the visual interpretation of the behavior of physiological variables and the inferred results.

The organization of this work is as follows: Section 2 defines the concepts related to the work carried out, Section 3 outlines the methodology of the proposal, Section 4 details the results achieved, and finally, Sections 5 and 6 explain the discussion and conclusions of our research.

2 Literature Review

This section describes the basic concepts necessary to understand the development of our work, as well as the theoretical framework that supports the techniques and methodologies used.

2.1 Fuzzy Logic

Fuzzy logic, proposed by Lotfi Zadeh, is a widely used technique for handling imprecision and vagueness that can arise in complex environments. It's a reasoning approach that mimics human decision-making by allowing truth values between 0 and 1, instead of the strict true/false division of traditional binary logic. This technique uses If-Then rules and fuzzy inference to process inputs expressed as a spectrum and produce outputs by converting fuzzy values into precise ones through a process called defuzzification.

Fuzzy logic has key components, including fuzzification, which transforms precise inputs into fuzzy values; an inference engine, which aids in rule evaluation; and defuzzification, which converts fuzzy values back into normal values. This technique is widely applied in areas such as control systems, artificial intelligence, and medical diagnostics due to its ability to mimic human decision-making and work effectively with partial or noisy information [16, 17].

2.2 Artificial Neural Networks

Artificial neural networks (ANNs) are an intelligent computing model inspired by the structure and function of the human brain. They recognize complex patterns and make predictions by processing input information through layers of interconnected nodes called neurons.

Each neuron applies a nonlinear function to a weighted sum of the inputs, and the network learns by adjusting these weights during a training phase to minimize the difference between predicted and desired outputs.

This technique can have multiple layers, known as input, hidden, and output layers, with deeper networks enabling the learning of more complex features.

Types of ANNs include feedforward networks, recurrent networks, convolutional networks, and specialized architectures such as generative adversarial networks (GANs) and long short-term memory networks (LSTM). These artificial neural networks are widely used in fields such as image classification, natural language processing, time series prediction, and other machine learning applications [18, 19].

2.3 Modular Neural Networks

Modular neural networks (MNNs) are artificial neural networks composed of multiple independent modules, each specialized in performing a specific subtask within a larger overall task, each module operates with its own input and processes it independently, without interacting with other modules.

An intermediate or control mechanism integrates the outputs of the modules to produce a final network output. This structure allows for specialization, scalability, flexibility, and improved performance by breaking down complex problems into smaller, more manageable components. Modular networks are inspired by the modularity of biological neural systems and can consist of different types of modules, such as feedforward, recurrent, or self-organizing neural networks [20, 21].

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2.4 Ambulatory Blood Pressure Monitoring

Ambulatory blood pressure monitoring (ABPM) is a non-invasive study performed with a device connected to a blood pressure cuff that records a patient's blood pressure and heart rate readings at intervals, typically every 15 to 20 minutes during the day and every 30 minutes at night, over a 24-hour study period that encompasses sleep, wakefulness, and daily activities. This technique offers greater predictive capacity for cardiovascular risk compared to measurements taken individually in a doctor's office, as it supports the analysis of the nocturnal blood pressure profile, the detection of masked hypertension or the "white coat" phenomenon, and the evaluation of circadian blood pressure variability [22–24].

2.5 Hypertension and Nocturnal Blood Pressure

Hypertension, or high blood pressure, is a sustained elevation of blood pressure in the arteries and is a key risk factor for cardiovascular disease, stroke, and premature death. The nocturnal blood pressure profile reveals how blood pressure varies during sleep; when this nocturnal dip does not occur ("no-dipping") or when blood pressure rises during the night, the cardiovascular risk increases significantly [25–30].

3 Methodology

Our proposal focuses on developing a hybrid model that implements neural networks and fuzzy logic to provide a comprehensive assessment of the risk of developing hypertension and cardiovascular events. Through various stages, both monolithic and modular neural networks, as well as fuzzy classifiers, have been developed and refined to combine the nonlinear learning capabilities of neural networks with the interpretive reasoning characteristics inherent in fuzzy logic. Figure 1 presents the proposed model.

Each component used in the model has been optimized using different bio-inspired algorithms, such as the Flower Pollination Algorithm (FPA),

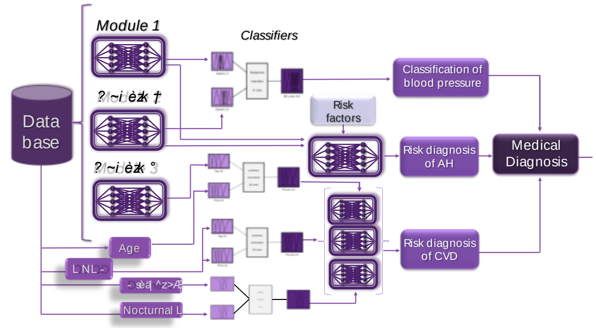

Fig. 1. Proposed model

Particle Swarm Optimization (PSO), Bird Swarm Optimization (BSA), Crow Search Algorithm (CSA), and Chicken Swarm Optimization (CSO). These methods were implemented both to adjust the membership functions in the fuzzy systems and to optimize the hyperparameters of the neural networks, such as the number of layers, number of neurons per layer, learning rate, and epochs. Table 1 presents a summary of the fundamental characteristics of each module, as well as the optimization results obtained.

The first phase of the model is a modular neural network, designed to model the changing behavior of blood pressure. Each module processes one of the three fundamental physiological variables: systolic pressure, diastolic pressure, and heart rate.

These modules were optimized using the FPA and BSA algorithms, achieving accuracy rates of 96%, 98%, and 97%, respectively, with BSA showing the best performance.

The second phase of the model includes fuzzy classifiers designed to classify the nocturnal profile of blood pressure and heart rate. The first classifier uses the ratio between systolic and diastolic blood pressure as inputs, achieving 88% accuracy after optimization with CSA. In the second classifier, the input variables are age and heart rate trend, achieving 100% optimal classification accuracy with CSO.

Finally, the model works with two additional neural modules designed to assess risks. The first model evaluates the risk of developing hypertension, considering risk factors such as blood pressure, whether the patient is a smoker, whether there are family members on

doi: 10.13053/CyS-30-1-6334

ISSN 2007-9737

Table 1. Summary of optimizations performed in entire model

Submodel	Detailed
Monolithic NN	Hypertension (4 yrs) Optimization: FPA Accuracy: 100%
Modular NN	Cardiovascular risk (10 yrs) Optimization: FPA Accuracy: 100%
	Blood Pressure Trend Optimization: BSA Accuracy: Systolic: 96% Diastolic: 98% Heart Rate: 97%
Fuzzy Classifiers	Type: Mamdani Hearty Rate Optimization: CSO Accuracy: 100%
	Type: Mamdani Nocturnal BP Optimization: CSA Accuracy: 88%

Fig. 2. Home window

anti-hypertensive treatment, and body mass index. This model achieves 100% accuracy after optimization using FPA. The second module, which corresponds to a modular neural network, assesses the risk of having a cardiovascular event and determines the equivalent cardiac age, also achieving 100% accuracy with the same algorithm.

The results obtained confirm the good performance of the proposed model, with the FPA and BSA algorithms achieving high performance in neural network optimization, while CSA and CSO showed greater stability and accuracy in fuzzy system calibration. This behavior indicates that the balance between global exploration and local exploitation of bio-inspired methods contributes to improving the predictive capacity and robustness of the model in the face of physiological variability in patients.

4 Results

To facilitate intuitive and efficient interaction between experienced users and the neuro-fuzzy hybrid model, a graphical user interface (GUI) has been developed to improve the system's practical use. The application, named Soft Diagnosis, was developed in C# within the Windows Forms ecosystem and is organized into six functional modules, which five of these modules allow for the individual execution of specific diagnoses for each subsystem, allowing users to consult only the relevant section of the model for analysis.

The initial window, which displays the system name and a clock indicating the current time is illustrated in Fig 2. The left sidebar contains the main menu, through which the user can efficiently access the various diagnostic modules.

Fig. 3 also presents the version with a light theme, designed to provide a more comfortable experience. This option allows users to select between light and dark mode via a switch located in the upper right corner.

The first module, which displays the name of the active section along with its corresponding icon in the top bar, allowing the user to immediately identify the module they are using is presented in Fig. 4. This section has been designed for loading and analyzing records obtained from Ambulatory Blood Pressure Monitoring (ABPM). Clicking the "Open" button will select the file corresponding to the patient, once the loading is complete, the interface automatically reveals the information, excluding personal data for confidentiality reasons.

Choosing the "Calculate" option activates the neural network responsible for estimating the blood pressure trend, while the associated fuzzy classifier determines the corresponding level. In

ISSN 2007-9737

Fig. 3. Light mode of the Initial Window

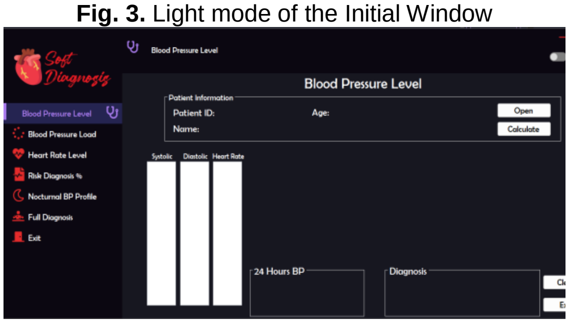

Fig. 4. Blood Pressure Diagnosis Module

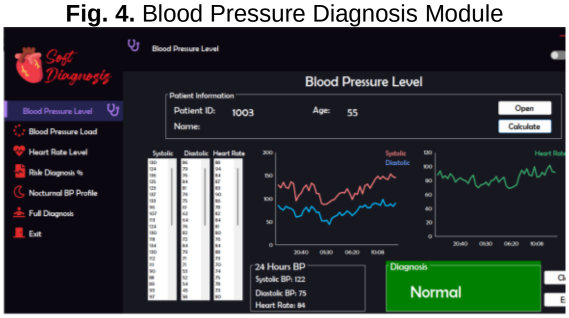

Fig. 5. Complete diagnosis of Blood Pressure Classification

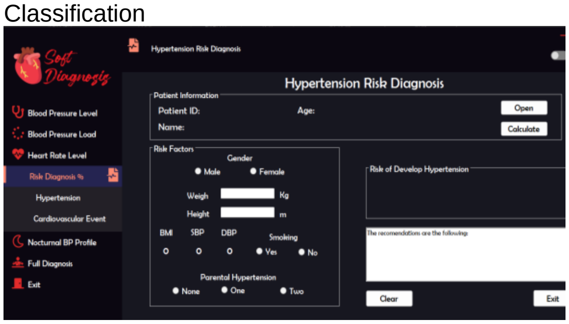

Fig. 6. Hypertension Risk Diagnosis Module

this way, the user obtains an accurate diagnosis that integrates both the dynamic behavior of the signal and the interpretation of the fuzzy system.

This module represents the initial phase of the hybrid model, establishing a direct connection between clinical data and the intelligent components that make up the neuro-fuzzy architecture.

Once the calculation is complete, the interface displays the reading history, along with its graphs and the trend estimated by the modular neural network.

This representation facilitates exploratory analysis and allows for visual comparison of blood pressure and pulse trends, contributing to the identification of significant variations in the records.

Additionally, the fuzzy classifier displays blood pressure level using a color-coded label, in the example, the value is displayed in green, indicating that it falls within the normal range. The module in operation illustrates in Fig. 5.

The design of the module intended for assessing the risk of developing hypertension within four years is presented in Fig. 6. This design incorporates additional variables and a monolithic neural network optimized for accurate risk estimation.

Additionally, to the individual analysis of each subsystem, Soft Diagnosis includes a module that integrates the patient's overall information to generate a comprehensive diagnosis.

The corresponding interface is shown in Fig. 7, similar to the previous modules, the process begins with selecting the file corresponding to the patient, but, for this, additional clinical information is required, including gender, smoking habits, presence of diabetes, antihypertensive treatment, family history, and usual sleep schedules.

This data allows for the evaluation of the circadian dynamics of blood pressure and complements the inference criteria.

Once the information has been entered, the system creates behavioral graphs and automatically activates each of the modules that make up the hybrid model.

This allows for a comprehensive evaluation of the patient's cardiovascular status, based on both physiological recordings and the combined inference of neural networks and fuzzy classifiers.

Fig. 8 presents the interface of the complete diagnosis, which shows the synthesis of results and the final health status assessment.

Fig. 2. Full diagnosis patient result

Fig. 3. Full Diagnosis Module

The complete diagnosis is defined as a global evaluation resulting from the interaction between the various modules of the system. This is evaluated on a particular set of variables, including blood pressure, heart rate, sleep habits, and clinical history.

5 Discussion

With the results obtained, we demonstrate that combining soft computing techniques, such as neural networks and fuzzy logic, establishes an effective methodology for the timely and accurate diagnosis of the risk of developing hypertension and cardiovascular events over time.

A modular structure is proposed, allowing the problem to be analyzed from a hierarchical perspective, where each component is responsible for processing specific physiological information, providing a partial diagnosis that is integrated into a complete evaluation.

The application of bio-inspired algorithms to the model has been essential for optimizing the accuracy of the results provided by the modules. The FPA and BSA have demonstrated remarkable capacity in optimizing the hyperparameters of the neural networks, achieving accuracy rates of 96% to 100%. Furthermore, the CSA and CSO demonstrated efficient fitting of membership functions in fuzzy systems, showing stability and consistency in the classification of complex physiological profiles. The combination of global exploration, characteristic of methods like CSA and FPA, with local exploitation, represented by BSA and CSO, facilitated the identification of optimal solutions, reducing overfitting and improving the system's generalizability. This clearly demonstrates the importance of applying both global and local search mechanisms in contexts of high data variability.

Regarding practical implementation, the graphical user interface called Soft Diagnosis is a significant contribution to our work, as it allows the hybrid model to be applied to clinical and educational practice. It features a modular structure, emphasizing the visual presentation of results, as well as the integration of files derived from ABPM, making the system a valuable tool for supporting medical decision-making. This tool is accessible and has the potential to expand to multiplatform environments, as demonstrated by its C# version currently under development.

6 Conclusions

The presented proposal has demonstrated that combining deep learning with approximate reasoning can increase the accuracy of cardiovascular diagnoses. Furthermore, optimization using bio-inspired algorithms demonstrated improvements in both the convergence of neural training and the accuracy of fuzzy system parameter tuning, creating a model that achieves performance levels exceeding 95% in all evaluated modules. Additionally, the implementation of the Soft Diagnosis graphical user interface enhances the project's practical applicability, enabling expert physicians to interact directly with soft computing techniques and obtain interpretable results. This also supports the improvement of the medical evaluation process by facilitating the integration of intelligent models into medical and academic practice.

Future work includes incorporating modules for generating clinical reports, as well as integrating a structured database for storing clinical histories, measurements, and diagnoses. The aim is to redesign the graphical user interface with a multi-platform approach, incorporating improvements in the user experience (UX/UI), such as the integration of a hamburger menu, a home screen and a secure login system. This transition will be made to the Python programming language, which facilitates its compatibility with open artificial intelligence environments and its integration with real-time data acquisition devices. Also, other applications could be considered, as in [31-32].

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Article received on 31/10/2025; accepted on 15/12/2025.
**Corresponding author is Patricia Melin.*