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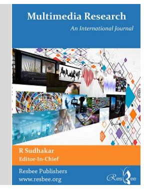

A Novel Enhanced Modular-Based Neural Network Framework for Effective Medical Diagnosis

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Abstract: Medical diagnosis is a common term used in describing the activities or processes involved in detecting, recognizing, or predicting disease or a group of diseases a patient suffers based on some symptoms and signs exhibited by the patient. The job of a medical practitioner in course of disease diagnosis involves gathering or acquiring symptoms and signs, often from different sources and forms, for analysis and thereafter diagnosis or prognosis. This task is complex due to the heterogeneous and overlapping nature of symptoms and signs and comorbidity of many diseases which often results in errors in accurate diagnosis, misdiagnosis, or under diagnoses. The main objective of this research is to propose a prototype architectural framework based on modular programming principles and that of the operations of the parallel processing design with Flynn's taxonomy of parallel processing. It is believed that several heterogeneous sources datasets can be simultaneously processed concurrently, and a final result presented.

Keywords: Modular Neural Networks, Medical Diagnosis, Under Diagnoses, Over-Diagnosis, Misdiagnosis

1. Introduction

In medical sciences, one of the major tasks of practitioners is the diagnosis of diseases in patients. The 17] define medical diagnosis as “a process of assigning a label to an illness or other problems by determining observations and symptoms”. The method in [3] affirm this stating that it also implies “all activities or processes involved in detecting, recognizing, or predicting a disease or a group of diseases a patient suffers based on some symptoms and signs exhibited by the patient.” Medical Diagnostic processes can be complex due to factors such as non-specificity of data, overlapping and heterogeneity of clinical data (signs and symptoms), and comorbidity of diseases. These, in addition to human errors, make the process extremely error prone with problems of underdiagnoses, over-diagnoses, or misdiagnoses, common, especially in developing countries where modern facilities are lacking with much dependence on manual methods. Often, these diagnostic errors cause more deaths than the effect of the diseases because; wrong prescriptions can be administered which results in other complications in the patient. To solve these problems, several mathematical models which are based on statistical distributions, regression models, and Artificial Intelligence techniques, are applied. In this research, the focus is on a machine learning algorithm known as Artificial Neural Networks (ANN).

ANN which is an example of an Artificial Intelligence algorithm provides a powerful tool to tackle complex problems such as medical diagnosis [4] and [12] because there is no need to provide a specific algorithm on how to detect a disease and their solutions are not restricted to linear or non-linear forms [2]. ANN has been successfully used by scholars for solving complex problems such as medical diagnosis. Examples include Multi-Layer Perceptron (MLP) with Back Propagation Algorithm (BPA), Self-Organizing Maps (SOM), Learning Vector Quantization (LVQ), Radial Basis Functions (RBFN), Convolutional Neural Networks (CNN), Recurrent Neural Networks, Neuro-fuzzy networks, and so on [5]. Common among the ANN techniques is that each scholar tends to use different types of fundamentals in training and learning data and representation of knowledge. Moreover, many of these are designed to work monotonically and specifically for the diagnosis of a particular disease, like diabetes mellitus, cancer, depression, etc., at a time. Also, and importantly, a limited amount of data can be handled by a monolithic ANN technique, hence limiting their capabilities. With the increasingly large amount of data generated daily; and the level of the complexity of problems in recent times, an

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integrated system where multiple ANN techniques are modeled into a single system to overcome the problem of fixed data attributes for the input layer of an ANN, handling heterogeneous data complexity problems, a multi-objective diagnostic system is very important. The use of modularity in ANNs for problem-solving is seen and proposed as a solution.

However, as learning problems grow in scale and complexity, and expand into multi-disciplinary areas, a more modular method for scaling ANNs is needed. A type of neural network that embodies the concepts and principles of modularity as used in structured programming and other modern software development techniques is the Modular Neural Network (MNN) [13]. As modularity is the property of a system whereby it can be broken down into a number of relatively independent, replicable, and composable subsystems (or modules), modular neural networks, essentially is a neural networks that can be decomposed into a number of subnetworks or modules. Each subsystem can be regarded as targeting an isolated subproblem that can be handled separately from other subproblems. The criteria for this decomposition may differ from one system to another, based on the level at which modularity is applied and the perspective of decomposition.

In this research, we examine an MNN which is a variation of a Neural Network. MNN is a type of ANN that exploits modularity in problems such that the overall problem is divided into several subtasks making it elementary, simpler, and less complex to solve. The neural networks on the different subtasks also known as modules are solved independently and the results obtained from each module are integrated to provide the final solution. MNN draws strength from each neural network type complementing the weaknesses of one another. Despite interests in neural network modularity, previous research has generally focused on particular MNN models and has lacked systematic principles and a broad general perspective on the topic as well as a lack in terms of a systematic analysis of the advantages and disadvantages of different approaches, with an increased focus on empirical comparisons of very specific models. Even for theoretically focused reviews, the taxonomy is sparse and fails to capture important properties and abstractions. Moreover, the scope of modularity focus is very narrow, ignoring important forms of modularity rather than focusing mainly on ensembles and simple combinations of models. These limitations need to be addressed if modularity is to be applied more generally. More general insights and a toolbox of modularity-related techniques are needed for consistently implementing successful MNNs. Fortunately, recent MNN techniques have been devised and revisited, especially in the last decade after the revival of the ANN field in the form of deep learning.

Qiao et al. [10] listed some advantages of MNN as extensibility, engineering economy (implementation and maintenance), reusability, and enhanced computability. Despite the successes recorded in the use of it, there are common gaps that need to be filled. For instance, common amongst all ANN types is the use of different types of fundamentals in training and learning data and representation of knowledge. Moreover, most are designed to work monolithically and specifically for the diagnosis of a particular disease at a time that limits their capabilities. A monolithic ANN technique can handle a limited amount of data. There is also the problem of having a fixed set of input data in a model. In practice (in an emergency situation), a physician does not wait until all clinical datasets are available before making decisions. They make do with available data to solve the problem. A model should adapt to the dataset available, not the other way around. In recent times, the amount of data that is generated daily is on the increase; and the level of complexity of problems is troubling, thus an integrated system where multiple ANN types are modeled into a single unit will help reduce, if not solved the identified problems. In this research, we examine the idea behind the existing Modular Neural Network (MNN) and propose a newly designed framework that could assist in providing an effective, efficient, and timely medical diagnosis. The main contribution of this work is to present a prototype architectural framework on the basis of the modular programming principles and that of the operations of the parallel processing design with Flynn's taxonomy of parallel processing. It is believed that various heterogeneous sources datasets can be concurrently processed simultaneously, and a final outcome is presented in this work.

The organization of the paper is arranged as follows: Section 2 describes the literature review, and section 3 defines the methodology. In addition to this section, 4 describes the discussion of findings. Finally, section 5 illustrates the conclusion section and future studies.

2. Literature Review

Several kinds of research have been conducted in the area of modularization of neural networks. For instance, Vazirani et al. [15] developed a modular neural network using 2 neural network models (that is, Backpropagation Neural Network (BPNN) and Radial Basis Function Neural Network (RBFNN)). An accuracy of 87.02% over training data and 85.88% over testing accuracy was obtained.Kaka et al. (2010) developed an MNN model that integrates three different ANN models using the Multi-Layer Perceptron (MLP), the Self-Organizing Maps (SOM), and the Radial Basis Function Neural Network (RBFNN).

Thereafter, the results are given to the central integrator. The integrator has a voting mechanism that is done in favor of the classes and the class that gets the maximum vote is declared the winner. This is pictured in the diagram of Fig. 1.

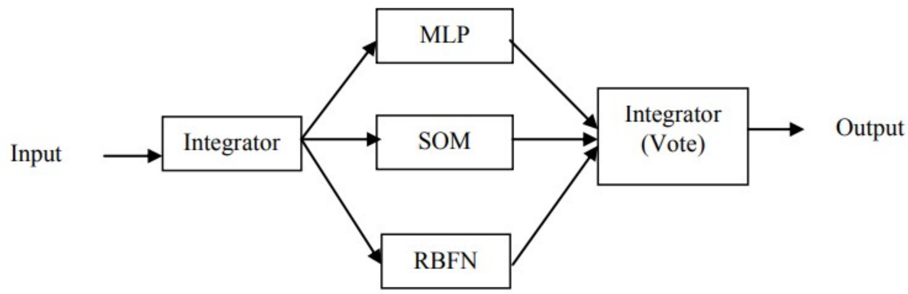

Fig.1. *Architecture of the Modular Neural Network (Source: Kala et al. [6])*

Also, a general framework was developed by Scardapane and Lorenzo [11] to train neural networks in a distributed environment, where training data are partitioned over a set of agents that communicate with each other through a sparse, possibly time-varying, and connectivity pattern. In another study, Melin et al. [8] developed a hybridized version that combines modular neural networks with fuzzy logic to provide hypertension risk diagnosis of persons. They proposed two fuzzy inference systems for the model. Sitirov et al. (2018) proposed an 'inter-criteria' analysis (ICA) method for studying the modular neural network technique. Alzubi et al. [1] designed a heuristic tubu optimized sequence modular neural network (HTSMNN) for the diagnosis of Parkinson's disease. Data on patients' brain activities were collected through a wearable IoT mental health sensor and the model was used for processing. Valera-Santos & Melin [14] described a new hybrid technique based on MNN with fuzzy logic integration for the diagnosis of pulmonary diseases like pneumonia and lung nodules. They analyzed images from digitized chest X-rays using classification approaches. The model divided features to achieve specialized analysis in modules of digital image analysis and classification.

An intelligent system should do more in the area of adapting to whatever limited data attributes are available, and not the available data, adapting to the system. Also, an intelligent system should not be dedicated to the diagnosis of a specific disease rather it should be able to handle a variety of diseases. From the reviewed literature, the following gaps were identified:

a. Most MNN input data attributes (i.e., signs and symptoms) have a fixed number and are targeted at a specific disease. In reality, the number of signs and symptoms vary and all must not be available for a physician to carry out a diagnosis. It is rather dynamic.
b. The input data items are usually homogeneous rather than heterogeneous. This indicates that scholars consider more data harvested from the same source rather than data sourced from multiple sources. In reality, clinical data are heterogeneous. For instance, data for facial expression analysis, Image processing, voice analysis, online activity analyse behavioural oral/cognitive analysis, and interview analysis cannot be sourced through the same medium and are not of the same format; hence cannot be processed with the same method. Most NNs, therefore, tend to isolate these problems and solve them independently.
c. There is no existing universally accepted standard for choosing the NN types that will be used in a modular neural network. Most scholars chose randomly and arbitrarily, or they just use the ones they are familiar with.
d. Most NN models are dedicated to solving a particular disease. Thus, most NN models are single-objective focused and fewer are multi-objective based. An intelligent model should adapt, be flexible, and be scalable to handle multiple related problems.

To overcome the problem of fixed data attributes for the input layer of the ANN, handling heterogeneous data complexity problems, and using a single model to solve multi-objective diagnostic problems is very important. The use of modularity in ANNs for problem-solving is seen as a panacea.

3. Methodology

In our methodology, we proposed an enhanced modular neural network architecture that incorporates the decomposition of the dataset into subtasks or modules as well as integrated multiple ANNs, selected based on their learning paradigm, i.e., supervised, unsupervised, and reinforcement framework based on the model used by Kala et al. in [6]. This will provide solutions to the listed gaps and also enhance the flexibility, adaptability, and better scalability of the system. It is presented in fig. 2.

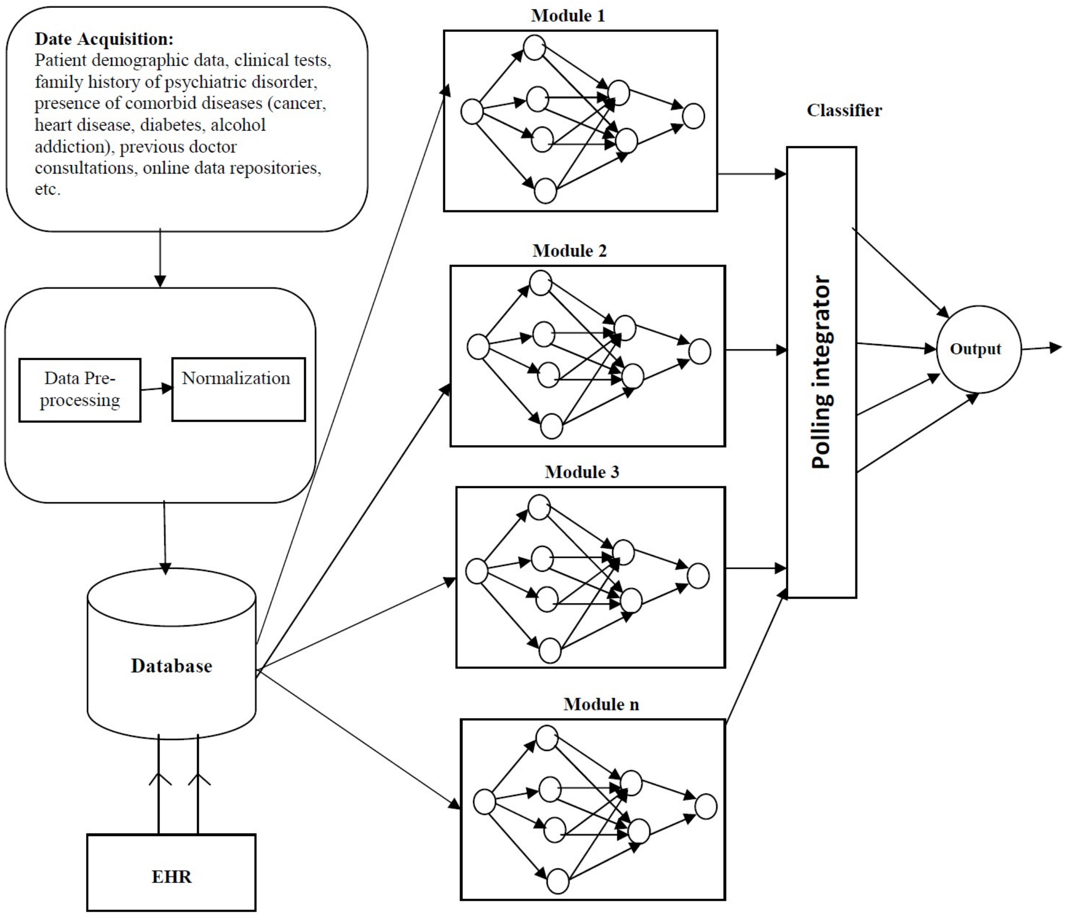

Fig. 2. General architectural model of the proposed enhanced MNN

In fig. 2, the architecture consists of a Data Collection Module (DLM), a Data Preprocessing Module (DPM), a Database Module (DBM), Modular Neural Network Module (MNNM), a Result Integrator Module (RIM). Each is responsible for a particular function.

From where symptoms and signs of the patient, usually from heterogeneous sources, are gathered. The Data Preprocessing Module (DPM) is where acquired data attributes are firstly decomposed into independent sub-units of sub-modules (e.g., demographic, historical, observed, interview, and laboratory datasets). Depending on the data attributes available, selected datasets can be pulled from each of the sub-modules(units) to form a pool of input datasets for processing. By this, the variability of input datasets of the model is achieved as the number of available data attributes can vary and not be fixed. In real practice, medical experts operate in a flexible and adaptable manner in that they draw symptoms and signs from heterogeneous sources for the diagnosis of diseases. Also, except in complex situations, physicians do not have to wait until all sets of data are available before carrying out the diagnosis. This scenario is more common in rural settings and poorly equipped hospitals. In monolithic ANNs, the data attributes are fixed and must all be available before the model can be put into use. This, however, negates the principle of flexibility, adaptability, and evolvability and makes the scalability of the model, impossible. An intelligent system should be flexible, adaptable, evolvable, and scalable, and by employing a system whereby the model adapts to the available dataset, not the data adapting to the model, the goal of artificial intelligence systems is enhanced. The selected data attributes are preprocessed in readiness for the training of the MNN model. The Database Module (DBM) stores the patient's demographic data, clinical tests, family history of the patient, previous doctor consultations, and other relevant data attributes.

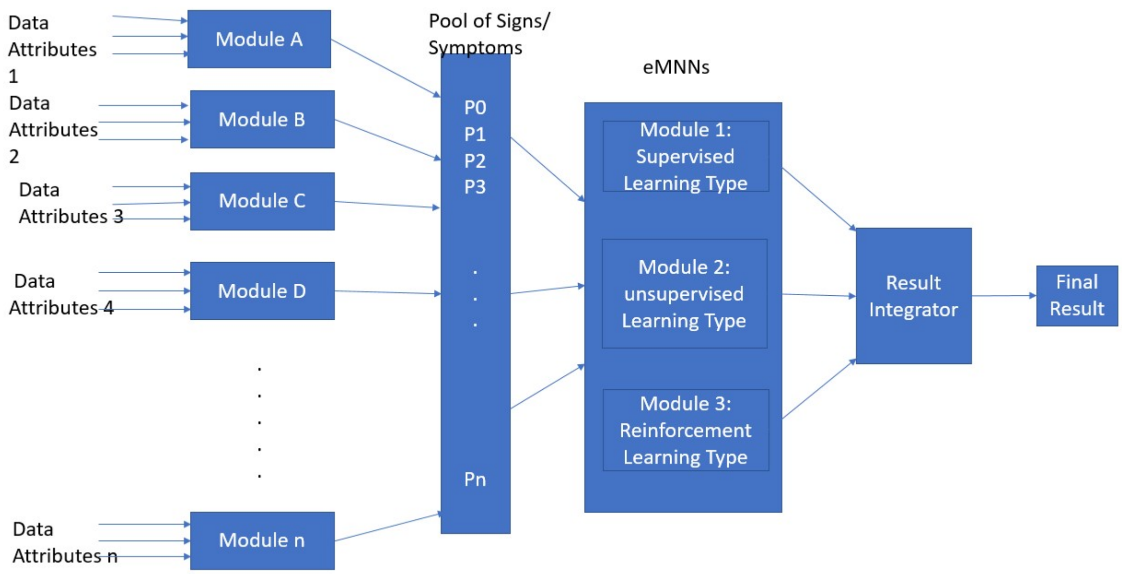

Fig. 3. *Architectural model of module decomposition*

3.1 Data Collection

Clinical data is heterogeneous and complex to handle. Medical practitioners do not acquire signs and symptoms from only one source but rather from multiple sources like facial expression, voice analysis, image processing, interview analysis, text analysis, activity analysis, color analysis, and so on. It may involve text, signals, and images like Magnetic Resonance Imaging (MRI), Position Emission Tomography (PET), CerebroSpinal Fluid (CSF), electrocardiogram (ECG), EEG, and Cardiac SPECT Liu, et al., [7] generated in huge quantities. Data collection is usually the first step and this starts from a mere sighting of the patient. In the most model, this visual aspect is not captured as part of the diagnostic processes.

3.2 Modular Decomposition

The decomposition of heterogeneous datasets into independent clusters of modules or units for data preprocessing and normalization. In this research, clinical datasets like symptoms and signs, Historical data, Scan and X-ray (brain scan) data, emotional data, facial expression data, voice recognition data, Activity recognition data, other tests like urine, saliva, stool, etc., are decomposed into independent modules or clusters for easy retrieval and processing. Fig. 3 illustrates the architectural model of module decomposition

3.3 Data Pre-processing Algorithm

Preprocessing of the data for each module independently. Data preprocessing is a module of data preparation, which defines any kind of processing carried out on raw data to prepare it for another data processing process. It has conventionally been a significant primary phase for the data mining process.

3.4 Data Normalization

This is to ensure that every value or vector of data attribute meant for input to the model is within a range of values suitable for processing. Also, this data normalization is the practice of arranging the data entries to assure they appear the same over all fields and records, which makes information easier to determine, group, and analyze.

3.5 Feature extraction Algorithm

A feature extraction algorithm is designed and employed to extract the appropriate features of any of the mental ailments with variable biomarkers. Feature extraction indicates the procedure to transform the raw data into numerical features that can be processed when preserving the information in the original data set. It produces better outcomes than applying machine learning directly to the raw data.

3.6 Genetic algorithm

A Genetic Algorithm (GA) is designed to initiate the weights that will be used in the artificial neural network. GA is a technique to solve both constrained and unconstrained optimization issues, which is based on natural selection, the procedure that drives biological evolution. The GA repeatedly modifies a population of individual solutions [9].

3.7 Training of the Networks i.e., Modular-based Neural Networks

Multiple types of artificial neural networks are selected according to their learning paradigm and integrated to form one block of a model. Each of the ANNs is given a separate module for solution computation. The different modules solve their part of the problem using their peculiar properties independently and parallel but simultaneously. There are three learning paradigms like supervised, unsupervised, and reinforcement learning paradigms in machine learning.

3.8 The Integrator

The solutions obtained from the independent ANN modules come to a central integrator. The integrator does the task of combining the results of the different modules and giving the final results which are the output of the system. In this case, the polling method is used. The results are subjected to a poll and the one with the highest vote is picked as the final result.

4. Discussion of Findings

The proposed system will add the following features to the existing system:

1. A mechanism for the decomposition of highly heterogeneous clinical data into clusters of independent datasets for processing in an ANN model.
2. A mechanism for drawing out data attributes from the independent clusters of the decomposed data for processing. This is in line with the ability of intelligent systems, not the have fixed data items that must be available for processing before decision-making processes can commence. They rather make do with available data attributes for processing.
3. Integrating multiple ANN types considering the type of data items they operate on and the type of machine learning paradigm (supervised, unsupervised, and reinforcement learning). This is because complex problems are handled by a team of experts who bring their experiences and unique expertise and skills together to solve the problem. This gives a more universally acceptable and better result.

A mechanism for diagnosis of multiple diseases in one model. Most diseases especially mental health issues are comorbid. They co-exist with other diseases in an individual's body, therefore a mechanism for diagnosing mental and physical diseases concurrently affecting the human body is required.

5. Conclusion and Future Study

We have presented a modular-based neural network model as a decision support system for the diagnosis of diseases based on their signs and symptoms. The proposed system framework introduces a means of decomposing clinical datasets into independent subsets called modules following their source and format or structure. It can also be decomposed according to the type of disease we intend to diagnose. Take, for instance, images (video or pictures) for facial expression analysis, ECG for voice or rate of heartbeat analysis, and so on. In our future work, we intend to implement the model on mental and behavioral health datasets. The model will be trained and validated based on the dataset gathered and then a diagnosis will be conducted. The model will be implemented in an environment characterized by Windows 10 operating system, MySQL database management system, Matlab, and Java programming languages. Standard performance metrics will be used to evaluate the performance of the proposed model. The use of the proposed enhanced modular neural network will provide more flexibility, adaptability, and more especially, scalability to the system over monolithic intelligent systems. It will also provide the possibility of diagnosing multiple diseases with a single model. This system can be scaled or extended to cover the diagnosis of multiple diseases like depression, schizophrenia, and bipolar as well as physical diseases like diabetes, cancer, tuberculosis, cardiovascular as well as infectious diseases. Most diseases are known to be comorbid.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.
Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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