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# An Enhanced Modular-Based Neural Network Framework for Effective Medical Diagnosis

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**Abstract:** Artificial Neural Networks (ANNs) are a type of machine learning algorithms that are used to solve problems such as medical diagnosis. In recent times, the amount of data that is generated daily is on the increase and the level of the complexity of problems is troubling. ANN algorithms are commonly used to overcome these challenges are further faced with the problem of having fixed data attributes as a dataset for its input layer, the complexity of having heterogeneous datasets instead of homogeneous datasets,and having a single objective output layer instead of a multi-objective output layer that could enable the diagnosis of multiple diseases. This researchproposes an enhanced modular-based Neural Network algorithm that utilizes heterogeneous datasets drawn from multiple sources, decomposed and clustered into independent units, and then trained by ANNs selected according to their learning paradigms – supervised, unsupervised, and reinforcement learning, to provide an effective, efficient and timely medical diagnosis, especially in developing countries where modern facilities are lacking with much dependence on manual methods.Thus an integrated system with multiple ANN techniques modelled into a single unit is developed. The results show that the proposed approach has been significantly successful indealing with the aforesaid problem compared to other methods with a training accuracy of 0.905, Sensitivity of 0.917, and specificity of 0.923.

**Keywords**: Modular Neural Networks, Medical Diagnosis, Underdiagnoses, Over-Diagnosis, Multi-Objective

***Nomenclature***

| Abbreviation | Expansion |
|---|---|
| **ML** | Machine Learning |
| **ANN** | Artificial Neural Networks |
| **MNN** | Modular Neural Network |
| **MRI** | Magnetic Resonance Imaging |
| **DCM** | Data Collection Module |
| **DPM** | Data Preprocessing Module |
| **DBM** | Database Module |
| **EMNN** | Enhanced Modular Neural Network Module |
| **RIM** | Result Integrator Module |
| **PET** | Position Emission Tomography |
| **CSF** | Cerebrospinal Fluid |
| **ECG** | Electrocardiogram |
| **EEG** | Electroencephalography |
| **GA** | Genetic Algorithm |
| **AI** | Artificial Intelligence |
| **ABPM** | Ambulatory Blood Pressure Monitoring |
| **SOM** | Self-Organizing Maps |
| **MLP** | Multi-Layer Perceptron |
| **BPA** | Back Propagation Algorithm |
| **RBFN** | Radial Basis Functions Network |
| **LVQ** | Learning Vector Quantization |
| **CNN** | Convolutional Neural Networks |



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# 1. Introduction

In medical sciences, one of the major tasks of practitioners is the diagnosis of diseases in patients. The author [29] defines medical diagnosis as "Assigning a label to an illness or other problems by determining observations and symptoms". [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 are difficult due to factors such as overlapping and heterogeneity of clinical data (signs and symptoms), non-specificity of data, and comorbidity of diseases [31]. Apart from human error, the process is very prone to errors such as under diagnosis, over diagnosis, or misdiagnosis, which are widespread, particularly in developing nations with limited access to modern equipment and a heavy reliance on manual methods. [32]. As incorrect prescriptions might be written, leading to more issues for the patient, these diagnostic errors frequently result in more deaths than the actual effects of the diseases. Several mathematical models based on Regression Models, Statistical Distributions, and ANN techniques [33] [34][25] are used to handle these difficulties. This study focuses on the ANN machine learning algorithm.

ANN is an example of an AI algorithm that provides a powerful tool to tackle complex problems such as Medical Diagnosis, Image and Video Recognition, Natural Language Processing, Speech Recognition, Recommendation Systems, Autonomous Vehicles, Financial Forecasting, Robotics, Game Playing, Climate Modeling, Supply Chain Optimization, Drug Discovery [2]. There is not much specific algorithm to detect diseases and find solutions. Moreover, they are not limited to forms that are linear or non-linear. Scholars have employed ANN to solve complicated issues with success [36]. Examples include SOM, MLP with BPA, RBFN, LVQ, CNN, RNN, Neuro-fuzzy networks, and so on [37][38][7]. The researcher using ANN approaches tends to employ distinct kinds of essentials for training and learning data and knowledge representation. Furthermore, a lot of these are made to function monotonously especially for the diagnosis of one specific illness at a time, such as Diabetes mellitus, Cancer, Depression, etc. Furthermore, and this is crucial, a monolithic ANN approach can only handle a finite quantity of data, which restricts its potential. To address the issue of fixed data attributes for the input layer of an ANN, handle heterogeneous data complexity problems, and handle multi-objective diagnostic systems, an integrated system that models multiple ANN techniques into a single system is crucial given the volume of data generated daily and the complexity of problems in recent times. One potential option is to employ modularity in ANNs to solve problems.

In this study, we investigate an MNN, a type of neural network. MNNs are a kind of ANN that takes advantage of a problem's modularity to break the main task down into multiple smaller, more manageable tasks. The neural networks for the many subtasks, often referred to as modules, are solved separately, and the final answer is produced by integrating the outcomes of each module. Each form of neural network complements the shortcomings of the others, giving MNN its strength. Although neural network modularity has attracted attention, prior research has primarily concentrated on specific MNN models, lacking systematic principles and a broad, general perspective on the subject. It has also failed to conduct a systematic analysis of the benefits and drawbacks of various approaches, favouring empirical comparisons of highly specific models. Despite studies that are theoretically oriented, the taxonomy is inadequate and overlooks significant attributes and abstractions. Furthermore, the focus on modularity is quite limited, disregarding significant types of modularity in favour of concentrating mostly on ensembles and straightforward model combinations. If modularity is to be used more widely, these drawbacks must be overcome. To regularly execute good MNNs, more general insights and a toolkit of modularity-related strategies are required. Thankfully, newer MNN algorithms have been developed and reexamined, particularly in the past ten years following the ANN field's resurgence in the form of deep learning.

Extension, engineering economy (implementation and maintenance), reusability, and improved computability are just a few of the benefits of MNN that the author [18] mentioned. Even while its utilization has yielded success stories, there are still frequent gaps that need to be addressed. For example, all ANN types share the use of various fundamentals for training and learning data and knowledge representation. Furthermore, the majority have limited capabilities since they are made to function monolithically and just for the diagnosis of a single disease at a time. The quantity of data that a monolithic ANN approach can process is constrained. Another issue is that a model's input data is limited to a set. In real life, (during an emergency), a doctor doesn't wait to make decisions until all clinical datasets are available. To tackle the problem, they make do with the data at hand. The accessible dataset should be adapted to the model, not the other way around. An integrated system with several ANN types modelled into a single unit would help decrease and/or solve the highlighted difficulties because the amount of data created every day is increasing and the complexity of problems is concerning. In this study, we investigate the underlying theory of the current MNN and suggest a novel framework that may help provide a prompt, accurate, and efficient medical diagnosis.

The rest of this article is organized as follows: Section 2 is about the review of related literature where related researches to the topic of discussion are reviewed and gaps are spotted. In section 3, the materials and methods (methodology) and proposed MNN Architecture and model are described. Section 4obtains the result and Section 5 mentions the discussion of the result Section 7 discusses the pros and cons of the proposed model. Finally, Section 8 concludes and discusses some future research directions.

## 2. Literature Review

MNNs are a powerful and hierarchical concept inspired by the human brain. They decompose complex tasks into simpler sub-tasks, allowing for faster learning, better generalization, and interpretability [8]. These networks consist of multiple modules, each dedicated to a specific task or sub-task [20]. The modules can be selected and combined by a controller to construct a neural network tailored for a specific task [9]. The performance of an MNN can be assessed using proxies such as importance and coherence, which measure the significance and consistency of sets of neurons in the network [40]. They have shown advantages such as interpretability, evolvability, and improved performance compared to non-modular systems.

Several kinds of research have been conducted in the area of modularization of neural networks. For instance, In 2018, Melin *et al.* [13] developed a hybridized version that combines MNN with fuzzy logic to provide hypertension risk diagnosis of persons. They proposed two fuzzy inference systems for diagnosing hypertension risk based on age, risk factors, and blood pressure behaviour. The model was trained with data obtained from (ABPM) and incorporates fuzzy inference systems for classification purposes. The learning accuracy of the MNN was found to be 98% for the first module (systolic pressure), 97.62% for the second module (diastolic pressure), and 97.83% for the third module (heart rate).

In 2021, Valera-Santos and Melin [25] 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. The effectiveness of the chosen neural network approach is demonstrated through the presentation of classification accuracy results. The experimental results show that the hybrid model used for lung disease classification achieved good results on the dataset it was trained on, with a mean accuracy of 87.11 on the pneumonia problem.

In 2023, Bennani and Dacheux [28] focused on classification instability using modular learning approaches. The authors evaluated different architectures of modular learning for DCSS instability classification and demonstrated that modular learning improves performances compared to non-modular systems. They also presented an approach for data labelling and segmentation using self-training applied to shoulder arthroscopy images. The output of the weighted modular learning using probabilities from the gating module achieved almost perfect classification for DCSS instability.

In 2012, Pandey *et al.,* [41] implemented an MNN approach combined with genetic algorithms to improve the diagnosis of breast cancer with high accuracy. The MNN consists of individual neural modules, each trained with GA using the training set. The optimization process involves achieving optimal connections (weights) among the neurons in each module of the MNN using GA. After training, the approach was tested using the testing dataset, and this process was repeated fifteen times. The mean training accuracy and mean testing accuracy are calculated by averaging the number of correctly and incorrectly identified data vectors. The experimental results demonstrate that the proposed approach achieves a high training accuracy of 95.97% and a testing accuracy of 96.5% for breast cancer diagnosis.

In 1997, Ohno-Machado, L. and Musen, M.A., [42] presented a medical application of MNNs for survival prediction in patients with AIDS. The MNNs classify cases based on the probability of death in a certain year of follow-up, using demographic, clinical, and laboratory variables as inputs. The results of the modules were combined to produce survival curves for individuals. The performance of the prognostic index was significantly improved by combining certain combinations of NN modules. Calibration measurements are used to quantify the benefits of combining NN modules, and the paper provides insights into when and how NNs should be combined for building prognostic models.

In 2022, Ali *et al.,* [43] used a deep learning approach called Incremental Modular Network Synthesis (IMNS) for medical imaging applications, which leverages small data to learn generalizable and domain-invariant representations. It uses small network modules called SubNets to generate salient features for a specific problem. These sub-nets were combined in different configurations to build larger and more powerful networks. Only one new SubNet module undergoes learning updates at each stage, reducing computational resource requirements and aiding in network optimization. The output of the SubNet A convolution layers was calculated using a softmax operation, resulting in outputs in the range [0, 1].The output of the SubNet B convolution layers is also obtained using a similar process.

In 2019, Pulido *et al.,* [44] demonstrated MNN to classify a patient's blood pressure level, using systolic and diastolic pressure and pulse data. Initially, The MNN architecture was formed by three modules: one for diastolic pressure data, one for systolic pressure data, and one for pulse data. The Leven berg-Marquardt and scaled conjugate gradient back propagation training methods are used for the tests. The response integration was performed using the average method. The MNN model was designed to achieve accurate classification of blood pressure levels. The proposed method was validated with tests performed on 16 patients, and positive results were obtained for the MNN. Hypothesis tests were conducted based on the errors obtained with the MNN architecture using the Leven berg-Marquardt learning method to obtain the trend of the systolic pressure. The results are compared with linear regression models based on the obtained errors.

In 2021, Wang et al., [45] devised modular multi-modal architecture for automatically detecting Alzheimer's disease using audio and text-based features. It consists of four networks: A c-attention-acoustic network, a C-attention-FT network, a C-attention-embedding network, and a unified network that combines all features. Audio samples were transcribed using the Google cloud-based speech-to-text API to extract text-based features. Various audio features were extracted using standard packages. The C-Attention-Unified network with linguistic features and X-Vector embeddings achieves the best accuracy of 80.28% and F1 score of 0.825 on the test dataset.

### 2.1 Review

Table 1 portrays the dataset that is used in the existing research. We considered eight papers that used MNN for the process of the diagnosis of signal or multiple diseases in the human body. Each method has different heterogeneous or homogeneous datasets that are selected from the universal standard or through random choices that were explained in detail.

### 2.2 Research Gap

An intelligent system should do more in the area of flexibility and adaptation to available datasets and not the other way around. Also, an intelligent system should not be dedicated to the diagnosis of a specific disease rather variety of related diseases should be handled by a single automated system. It was observed from the reviewed literature that:

1. The input datasets of most MNNs have a fixed number.
2. The input datasets are usually homogeneous instead of heterogeneous as in real-world scenarios.
3. No existing universal standard for choosing the NN types to form the MNN. Researchers arbitrarily and randomly make choices without basing their choices on any standard method.
4. Most NN models are dedicated to solving a particular disease.

To overcome the problem of having to deal with static data attributes as input for the ANN model, handling the complexity problems of heterogeneous data, and solving multiple related problems with a single multi-objective model, the use of modularity in ANNs for problem-solving is a panacea. The paper therefore proposes an EMNN that teaches an optimized category hierarchy to decompose complex patterns and uses separate modules to process specific patterns.

## 3. Proposed Methods

Fig1 shows the architecture of the proposed system. The architecture consists of a DCM, DPM, DBM, MNNM, and RIM. Each is responsible for a particular function. This will provide solutions to the listed gaps and also enhance the flexibility, adaptability, and scalability of the system.

### 3.1 Data Acquisition

Handling clinical data might be challenging due to its heterogeneity [30]. Medical professionals gather signs and symptoms from a variety of sources, including activity analysis, facial expression analysis, voice analysis, image processing, text analysis, interview analysis, colour analysis, and more. It could involve massively generated text, signals, and images such as MRI, PET, CSF, ECG, EEG, and Cardiac SPECT [12]. The initial phase is typically gathering data, which begins as soon as the patient is seen. This visual component is not recorded as part of the diagnostic procedures in the majority of models. Electronic Health Records, Remote Patient Monitoring, Tele health and Telemedicine, and Mobile Health Apps are the recent methods that are used to collect the patient's details.

***Table 1.*** *Review of the Existing Method*

| Authors | Input data Set | Homogeneous/ Heterogeneous Dataset | Followed Universal Standard/ Random choices | To solve a particular disease/ Multiple diseases |
|---|---|---|---|---|
| Melin *et al.* [13] | A total of 300 ABPM studies were conducted, with 24 studies obtained from students with master's and doctoral degrees in computer science from the Tijuana Institute of Technology, and 276 studies provided by the Tijuana Cardio Diagnostic Center. | Heterogeneous Dataset | Based on testing different architectures and learning methods to obtain the best possible results. | Classification of blood pressure and hypertension risk diagnosis. |
| Valera-Santos and Melin [25]– | Three large datasets of Chest X-rays.<br>This dataset contains 247 images divided into 2<br>classes, having 154 images in the "'lung nodules" class' and 93 in the 'normal"<br>class',; the dataset which was created by the Japanese Society of Radiological Technology<br>(JSRT) | Heterogeneous Dataset | Randomly Selected | Pneumonia and lung nodules. |
| Bennani and Dacheux [28] | The dataset included a total of 840 photos, with 105 healthy DCSS images, 173 in stage 1, 187 in stage 2, and 375 in stage 3. | Homogeneous Dataset | Randomly selected | Dorsal Capsulo-Scapholunate Septum (DCSS) |
| Pandey et al.,[41] | The dataset used is the breast cancer data from the UCI ML repository for this purpose. | Homogeneous Dataset | Randomly Selected | Breast cancer |
| Ohno-Machado, L. and Musen, M.A., [42] | Subset of the ATHOS dataset that contains 914 patients. | Homogeneous Dataset | Randomly Selected | AIDS |
| Ali *et al.,* [43] | The paper utilizes three different datasets.<br>For malaria detection, a publicly available dataset provided by the NIH is used.<br>For diabetic retinopathy detection, the publicly available Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 blindness detection challenge dataset is utilized.<br>For tuberculosis detection, a publicly available Shenzhen chest radiograph dataset is used. | Heterogeneous Dataset | Randomly Selected | Malaria, Diabetic retinopathy, and Tuberculosis |
| Pulido *et al.,* [44] | A dataset of 300 patient samples is used for training all the modules. | Heterogeneous dataset | Randomly selected | Systolic pressure, Diastolic pressure, and Pulse. |
| Wang *et al.,* [45] | Cookie Theft picture description in the Boston Diagnostic Aphasia Exam. | Homogeneous dataset | Randomly selected | Alzheimer's Disease |

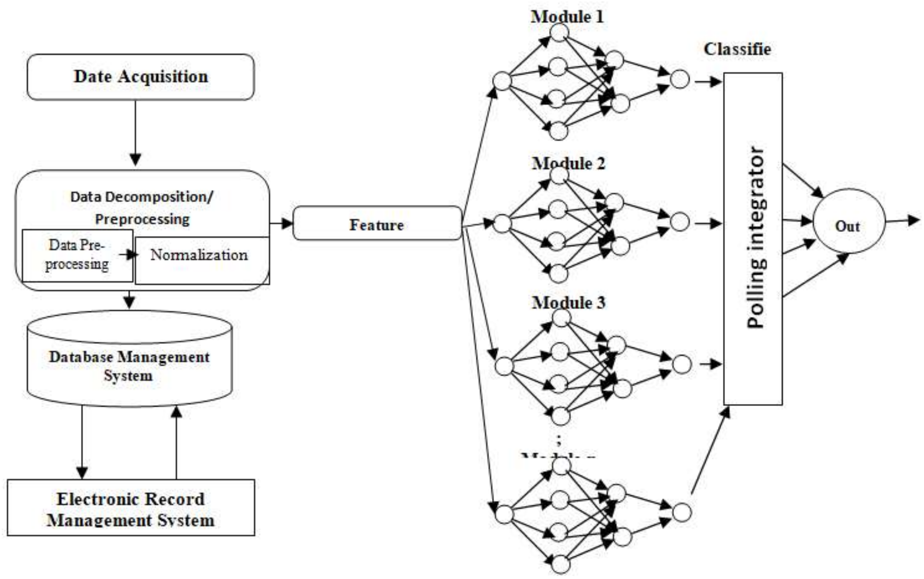



***Fig.1***. *An overview of the architecture proposed by MNN*

## 3.2 Data Decomposition/Preprocessing Module (DPM)

The Data is acquired from the world from heterogeneous sources and initially decomposed into independent sub-units of sub-modules. Oftentimes, all required datasets may not be available for processing. Depending on the data attributes available, selected datasets can be drawn from each of the sub-modules (units) to form a pool of input datasets for processing. This provides the possibility of having variable input datasets instead of the usual static or fixed set of input datasets in a neural network model. The following procedures are taken under the data decomposition and preprocessing phase:

1. **Modular Decomposition:** The division of diverse datasets into separate groups of units or modules to normalize and prepare the data. For ease of retrieval and processing, clinical datasets such as symptoms and signs, historical data, X-ray (brain scan) data, facial expression data, emotion data, voice recognition data, activity recognition data, and other tests like urine, saliva, stool, etc., are broken down into separate modules or clusters in this study.
2. **Data Preprocessing Algorithm:** Preprocessing of the data for each module independently. Each independent cluster or module undergoes specific pre-processing steps tailored to the characteristics of the data within that cluster [46]. Pre-processing may include cleaning, normalization, feature engineering, or other tasks necessary to prepare the data for analysis [47].
3. **Data Normalization:** This occurs to make sure that each value or vector of data attribute intended for the model's input falls into a processing-appropriate range of values. Typically, the range is between 0 and 1 [6]. It is an essential step in data-driven applications that impact model performance. Normalization is applied independently to each cluster or module based on the specific characteristics of that subset of data.
4. **Reintegration:** After independent pre-processing and normalization, the processed clusters or modules are reintegrated to reconstruct the complete dataset. This step involves combining the pre-processed subsets to form a coherent and normalized dataset.

The patient's clinical test results, family history, past medical consultations, demographic information, and other pertinent data elements are all stored in the DBM. It is software that makes managing, organizing, retrieving, and manipulating data in a database easier. It acts as an interface for managing, retrieving, and storing data effectively.

## 3.3 Feature Extraction

To extract the relevant aspects of any mental illness with changeable biomarkers, a feature extraction algorithm is created and used. This reduces the dimensionality of the data while retaining key information that is useful downstream. Initially, it starts with raw input data, which could be images, signals, or any other form of data. The raw input data is complex and contains a lot of irrelevant information, a dedicated feature extraction helps in simplifying the information and provides more focused inputs to each module. The choice of feature extraction method depends on the specific characteristics of the data and the requirements of the task. The common input data are images [5], text [4], and Signals [1] that needed feature extraction.

## 3.4 Enhanced Modular-based Neural Network

To create a single model block, several ANN types are chosen according to how they are learned and combined. To compute the solutions, distinct modules are provided to each ANN. The many modules work in parallel but concurrently to solve their portions of the problem by utilizing the unique qualities that set them apart from other modules. Each method made use of Subnets, which are tiny network components that can produce distinctive properties for a given issue. Then, by merging these Subnets in various configurations, we create ever-larger and more potent networks. Only one new Subnet module receives learning updates at a time. This helps with network optimization and lowers the amount of processing resources needed for training.

To get the solution to the medical problem initially suitable data are selected from the dataset and it will be sent to a neural network to obtain a suitable solution. The neural network is made up of layers of neurons. There are three layers in the neural network: The input layer, the Hidden Layer, and the output layer. The input layer receives the input and the output layer predicts the output. In between there is a hidden layer that performs the computation functions as required. Let's consider an image is taken for prediction. The image is composed of X by Y pixels which makes Z pixels. Which is represented in the vector pixel $x^t = (x_1, x_x, ..., x_n)$ Then each pixel is fed as an input to each neuron of the first input layer. The neurons of the first layer are connected to the neurons of the second layer through channels. Each channel is assigned a numerical value known as weight. That is represented as $w_i$, where $i = 1,2,3,...,n$. The inputs are multiplied by the corresponding weights and the sum is sent as an input to the neurons in the hidden layer. It is denoted as

$$z = (w_1, ..., w_n).\begin{pmatrix} x_1 \\ : \\ x_n \end{pmatrix} \tag{1}$$

Each of these neurons is associated with a numerical value called the bias which is then added to the input sum. Where B is represented as a bias

$$z = (w_1, ..., w_n).\begin{pmatrix} x_1 \\ : \\ x_n \end{pmatrix} + B \tag{2}$$

Then the value is passed to a threshold function called the activation function. The result determines the next neural activation. If it is active the data will be transmitted to that neuron through the channel for propagation through the network. This process is called forward propagation. In the output layer, the neurons with the highest value are determined as output probability. To obtain an accurate output, the output is trained along with the input. The input is compared against the actual output to realize the error in the prediction. The magnitude of the error indicates how wrong we are and the sign suggests the predicted value is higher or lower than expected. To obtain this the information is then transferred backwards through the network through back propagation. This process is iterated to perform with multiple inputs that are assigned such that the network can predict them correctly. However, for the signal and other data prediction, the characteristics of the data will vary along with the output.

## 3.5 Training of the Networks

The ANN algorithms chosen for training in each of the modules are drawn from the three learning paradigms of ML namely: supervised, unsupervised, and reinforcement learning paradigms.

### 3.5.1 Supervised Learning Paradigm

To make accurate predictions or classifications of new and unseen data we use supervised learning. The training dataset consists of input data and their corresponding output labels. The input data represent the features or characteristics of the examples, while the output labels represent the desired predictions or classifications. The algorithm adjusts its internal parameters (weight) during training to minimize the difference between its predictions and the actual labels. Finally, it may be fine-tuned by adjusting hyper parameters or retraining on a larger dataset to improve its performance. It is used in structured data, text, image, and Audio data.

### 3.5.2 Unsupervised Learning Paradigm

When the data is without any predefined output labels for the algorithm the output from the neural network moves to the unsupervised learning. Common techniques in unsupervised learning include clustering, dimensionality reduction, and density estimation. It can process text data, image, geometric, and network data.

### 3.5.3 Reinforcement Learning Paradigms

The reinforcement Learning paradigm is within ML where an agent learns to make decisions by interacting with an environment. It can process Raw Sensory Input, text, and State Representations. This method is well-suited for scenarios where explicitly labelled data is not available, and the agent must learn through trial and error by interacting with the environment.

## 3.6 Integrator

A central integrator receives the solutions that are obtained from the separate ANN modules. The integrator's job is to compile the output of the various modules and provide the final results, which are the system's output. The polling approach is applied in this instance. The outcome is put to a vote, and the winner chosen at random is the one with the most votes. Fig2 represents a detailed architecture of the EMNN proposed for the new system.

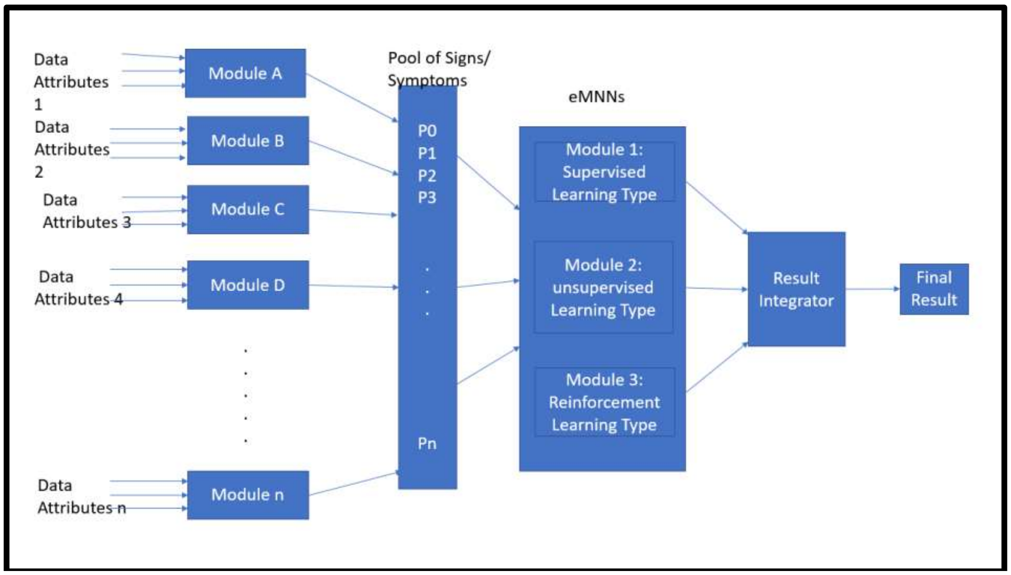


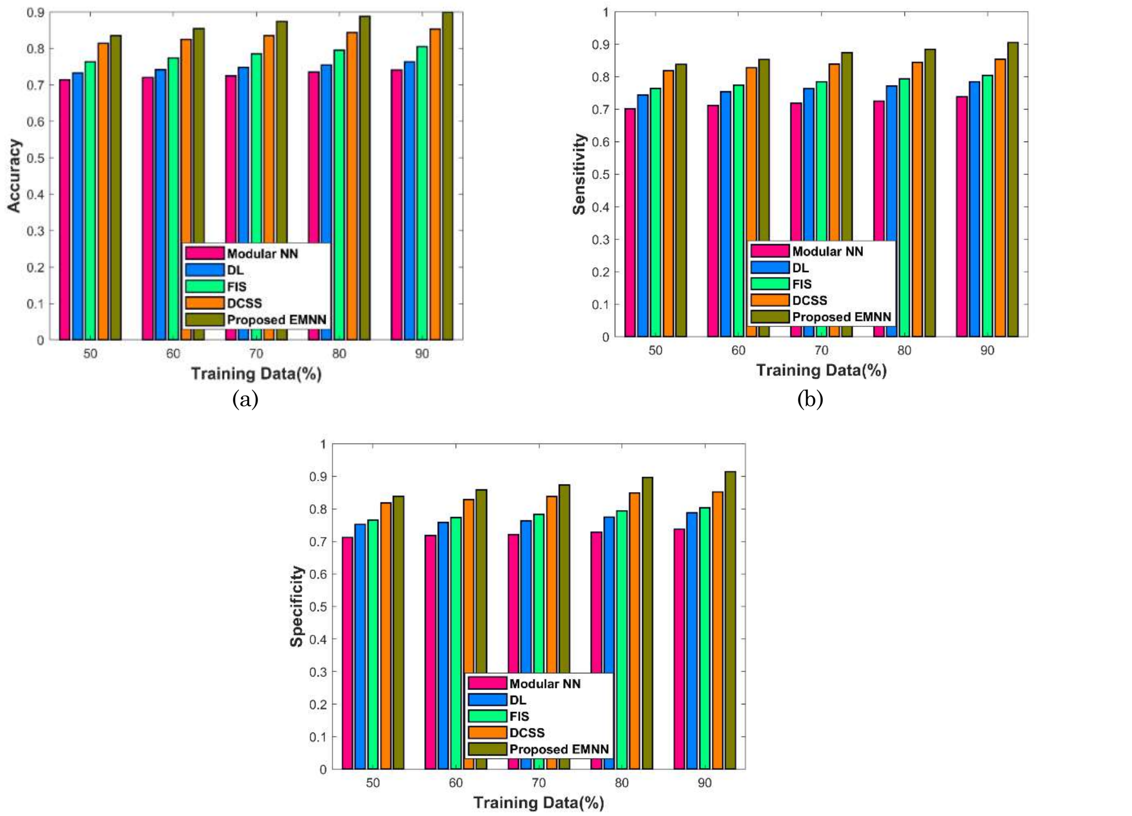

***Fig. 2***. *The architecture of the proposed EMNN*

# 4. Result

To evaluate the performance of the developed system, we compute the accuracy, sensitivity, and specificity of the EMNN. The training data and the K-value are compared with MNN [42], DL [43], FIS [13], and DCSS [25].

## 4.1 Comparative Analysis Based on Training Data

The comparative analysis of the proposed EMNN based on training data based on testing accuracy, sensitivity, and specificity evaluation for the data base is depicted. Fig 3a) Indicates the comparative assessment of accuracy by varying the percentage of training data. The testing accuracy of Enhanced MNN is 0.914, whereas MNN is 0.736, DL is 0.787, FIS is 0.803, and DCSS is 0.852for 90% of training data. The performance improvement of the proposed model with early devised approaches like MNN, DL, FIS, and DCSS is 17.59%, 15.03%, 10.47%, and 5.01%The comparative assessment of sensitivity with various values of training data is explained in Fig3 b). The sensitivity of the early models and Enhanced MNN is 0.736, 0.787, 0.803,0.852, and 0.914with 90% of training data the performance improvement of the proposed approach is 19.47%, 13.89%, 12.14%, and 6.78%. Fig 3 c) Shows the comparative evaluation of specificity by shifting training data. When the training data is 90%, the specificity of MNN is 0.736, DL is 0.787, FIS is 0.803, DCSS is 0.852, and Enhanced MNN is 0.914. The performance improvement of the proposed system is 19.47%, 13.89%, 12.14%, and 6.78%. with other existing methods.

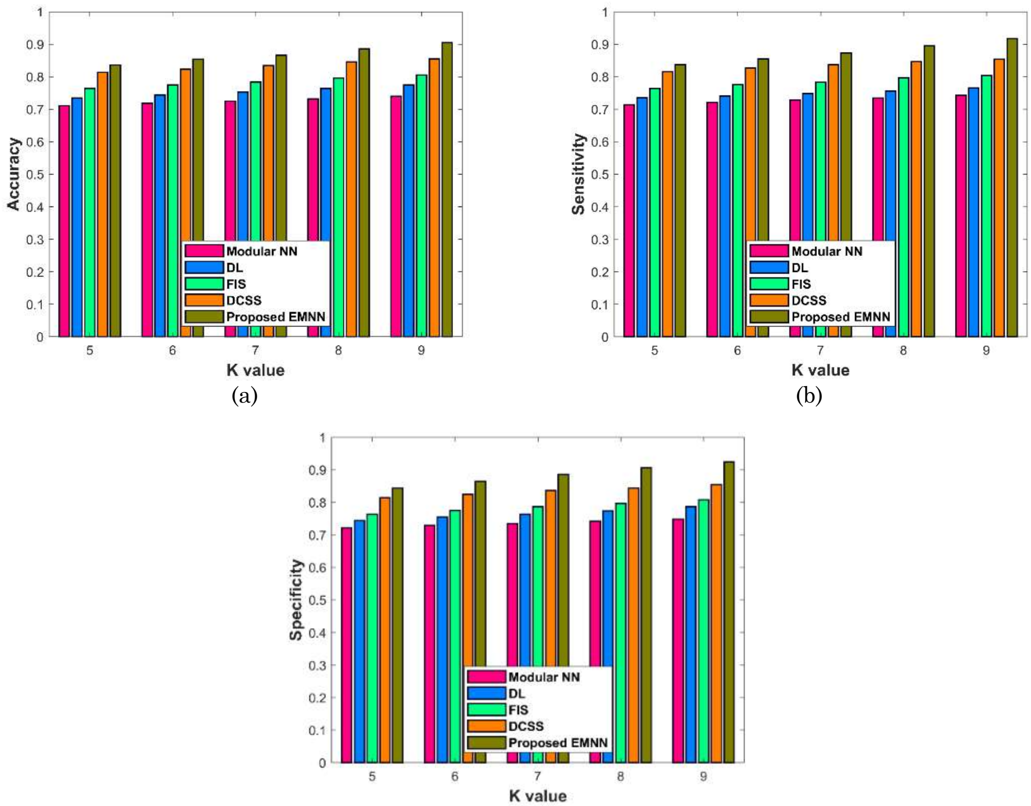



(a) (b) (c)

***Fig. 3.*** *Comparative analysis of Enhanced MNN by shifting training data percentage for a) Testing accuracy, b) Sensitivity, c) Specificity*

## 4.2 Comparative Assessment Based on K-Value

The comparative assessment of Enhanced MNN based on k-value with testing accuracy, sensitivity, and specificity for the database is illustrated in Fig4. The comparative evaluation of accuracy by varying training data percentage is explained in Fig4 a). Indicates the comparative assessment of accuracy by varying the percentage of training data. The testing accuracy of Enhanced MNN is 0.905, whereas MNN is 0.739, Deep learning is 0.774, FIS is 0.805, and DCSS is 0.854 for 90% of training data. The obtained improvement performance by the developed approach is 18.34%, 14.48%, 11.05%, and 5.64%. Fig4 b) Shows the comparative assessment of sensitivity by varying training data percentages. When training data is 90%, Modular NN is 0.742, Deep learning is 0.764, FIS is 0.803, DCSS is 0.854, and EMNN is 0.917. The performance improvement of the developed model is 19.08%, 16.58%, 12.43%, and 6.98% with other existing methods. Fig4 c) Shows a comparative assessment of specificity with various percentages of training data. The specificity of Enhanced MNN is 0.923, whereas the early devised models obtained Modular NN as 0.748, Deep learning as 0.786, FIS as 0.807, and DCSS as 0.854 for 90% of training data. The improvement in the performance of the introduced approach with Modular NN, Deep learning, FIS, and DCSS is 18.96%, 14.84%, 12.57%, and 7.48%.




(a) (b)

(c)

***Fig. 4.*** *Comparative Assessment based on k-value for (a) Accuracy (b) Sensitivity and (c) Specificity*

## 5. Discussion of Findings

The performance of the EMNN model for Medical Diagnosis is assessed using the results obtained from the computations based on the dataset and comparing it with MNN, DL, FIS, and DCSS, and the values obtained are presented in Table 2. In addition, the figured value is considered with 90% training data and the k-value is 9. Hence, the developed EMNN model attained accuracy, sensitivity, and specificity recorded of 0.905, 0.917, and 0.923 respectively, when considering the K-value is 9.

***Table 2.*** *Comparative discussion of the proposed method*

| Percentage | Variation | Evaluation metrics | MNN | DL | FIS | DCSS | Proposed EMNN |
|---|---|---|---|---|---|---|---|
| **90%** | **Training data** | **Accuracy** | 0.740 | 0.763 | 0.804 | 0.853 | 0.898 |
| | | **Sensitivity** | 0.737 | 0.784 | 0.804 | 0.853 | 0.904 |
| | | **Specificity** | 0.736 | 0.787 | 0.803 | 0.852 | 0.914 |
| **90%** | **k-value** | **Accuracy** | 0.739 | 0.774 | 0.805 | 0.854 | 0.905 |
| | | **Sensitivity** | 0.742 | 0.765 | 0.803 | 0.853 | 0.917 |
| | | **Specificity** | 0.748 | 0.786 | 0.807 | 0.854 | 0.923 |

Furthermore, the following characteristics will be added to the current system by the proposed system:

1. A method for dividing extremely diverse clinical data into separate dataset clusters so that an ANN model can process them.
2. A method for extracting data attributes for processing from the separate clusters of the decomposed data. This aligns with the capabilities of intelligent systems, rather than requiring fixed data items to be accessible for processing prior to initiating decision-making procedures. They would prefer to process the data using the qualities that are already accessible.

This is because, in real practice, decision support making and particularly, medical experts operate in a flexible and adaptable manner in which they draw symptoms and signs from heterogeneous sources for the diagnosis of diseases. In doing this, physicians must not have to wait until all datasets (i.e., signs and symptoms) are available before performing diagnosis. They must have to work with available datasets to achieve results of diagnosis for quick intervention. There is therefore the need for an intelligent system that can adapt and be flexible to operate with whatever available datasets to achieve results unlike in the monolithic ANNs whose input datasets are fixed and non-dynamic and must all be available before the model can be put into use. However, this defeats the idea of adaptation, flexibility, and evolvability and prevents the model from becoming scalable. The purpose of AI systems is improved by using a system whereby the model adapts to the available dataset, rather than the data adapting to the model. An intelligent system should be flexible, adaptive, evolvable, and scalable. To prepare the chosen data properties for MNN model training, preprocessing is done.

3. Combining several ANN types while taking into account the kinds of data items they work with and the ML paradigms (supervised, unsupervised, and reinforcement learning). This is because complicated issues are handled by a group of specialists who pool their diverse backgrounds, specialities, and problem-solving abilities to tackle the issue. This produces a better and more widely accepted outcome.

A method for diagnosing several illnesses with a single model. Most illnesses are comorbid, particularly mental health conditions. They coexist with other illnesses in a person's body, so a system for identifying illnesses that affect the body simultaneously—both physical and mental—is needed. This suggests that researchers take into account more information gained from a single source as opposed to information gathered from several sources. Clinical data are varied. For example, data cannot be sourced through the same media or be of the same format for facial expression analysis, image processing, voice analysis, online activity analysis, behavioural oral/cognitive analysis, and interview analysis. As a result, they cannot be processed using the same approach. As a result, most NNs tend to identify these issues and resolve them on their own.

# 6. Advantages and Disadvantages

## Advantages

a. The heterogeneous datasets drawn from multiple sources allow for a more comprehensive representation of clinical data.
b. This method enhances the system's capabilities and improves the accuracy of medical diagnosis.
c. The architecture allows extensibility, reusability, and enhanced computability, making it a flexible and scalable solution.
d. This method can handle complex medical problems.

## Disadvantages

a. The input datasets used in the proposed method are heterogeneous, which may not accurately represent real-world scenarios. It also requires high computation time and cost.
b. Most neural network models used in MNNs are dedicated to solving a particular disease anda broader range of medical diagnoses. However, this method is limited to basic prediction.

# 7. Conclusion and Recommendations for Future Study

We have presented an EMNN as a decision support system for the diagnosis of diseases based on their signs and symptoms. A method of breaking down clinical datasets into separate subsets known as modules based on their source, format, or structure is introduced by the proposed system framework. It can also be broken down based on the kind of illness we want to identify. Consider using photographs or videos to analyze facial expressions, an ECG to analyze heart rate or speech, and so on. This method can produce an accuracy of 0.9.5, a sensitivity of 0.917, and a specificity of 0.923. We plan to apply the model to datasets related to mental and behavioural health in our upcoming work. After the model has been trained and validated using the collected dataset, a diagnosis will be made. The Windows 10 operating system, My SQL database management system, MATLAB, and Java programming languages will all be present in the environment where the model will be implemented. The performance of the suggested model will be assessed using conventional performance criteria. Additionally, it will open up the option of using a single model to diagnose several diseases. The diagnosis of several illnesses, including diabetes, cancer, tuberculosis, cardiovascular, and infectious diseases, as well as mental illnesses including schizophrenia, bipolar disorder, and depression, can be covered by expanding or scaling this system. It is well-recognized that most diseases coexist.

The research's conclusions lead to the following recommendations:

1. Depending on the learning paradigm and the kind of data handled, several types of neural networks should be chosen to make up the EMNN.
2. A multi-objective strategy should be assumed by the system.

## 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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