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Pattern recognition using the multi-layer perceptron (MLP) for medical disease: A survey

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Abstract

In recent years, Machine Learning (ML) algorithms, especially Artificial Neural Networks (ANNs), have achieved remarkable success in various fields such as Pattern Recognition, Computer Vision, and Voice Recognition. Where ANNs algorithms have proven their superiority over traditional ML algorithms like (Support Vector Machines, Decision Trees, and Naïve Bayes) in various fields. Multi-layer Perceptron (MLP) network is one of the popular ANNs types and is used in various fields. The field of healthcare pattern recognition is considered one of the most important fields in our modern age, as this field is concerned with patterns extracted from raw data. There are many studies that dealt with MLP networks to detect and classify patterns in such a scope. In this study, a body of work deals with using the MLP networks for healthcare pattern recognition in five different topics (Diabetes, Heart disease, Liver, Breast cancer, and Parkinson's disease). The goal of the research is to identify strengths and weaknesses, and to identify the latest developments of adapting MLP network to recognize patterns in different data sets in the Healthcare field.

Keywords: Pattern recognition, Artificial Neural Networks, Multi-Layer perception, Healthcare, Pre-processing
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1 Introduction

All the developments that the world has witnessed in the past few years in the field of technology and the development of modern devices, as well as entering the electronic field with the development of equipment commensurate with the tremendous development in various fields, such as the medical field, the academic field, the field of industry, astronomical discoveries, down to matters related to human intelligence such as decision-making has developed by Artificial Intelligence (AI) [12]. All these areas were penetrated by AI and showed extreme accuracy in dealing with them. The idea of supporting the machine with enough intelligence makes it able to decisions making product huge savings with tools and capabilities as well as a notice decreasing in time consumption and costs. Today's machines are entrusted with great tasks where some of them do the monitoring and analysis operations while others are interested in the collection and statistical issues. In the same context, there are machines that interfere in more serious matters such as maintaining security and government policies.

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AI includes deep learning (DL) and ML [31]. Which in turn deals with more precise and specific patterns where developed coincide with spared of smartphones and mobile computing [39]. The researchers and engineers proposed several models and algorithms that could deal with data and extract information such as data mining methods [19]. In the same context, many models have been developed to generate roles and factors to provide classification or prediction to the given issue. The machine learning models deal with numerical data like (ages, dimensions, and weights) or descriptive data such as (colors and geometric forms), where the model creates role depending on the given data to generate a solution such as a decision tree, random forest [14] and naive Bayes [15]. On the other hand, Deep learning depends on images or videos to extract features for different patterns such as character and handwriting recognition [18], speech emotion recognition [5], speech and person detection [16, 27], etc.

In this survey, we will re-explain several research that interest with healthcare patterns [7] which have been solved by multilayer perceptron models (MLP). Healthcare pattern recognition falls under three stages: first is pre-processing, second is features extraction and the last one is a classification which uses different algorithms such as support vector machine (SVM) [17].

We studied the literature researches that served the healthcare pattern recognition. Among the huge amount of research 19 studies have been chosen for this study, the articles were in intervals [2019-2022], while the impact factor of journals takes into consideration. The topics of the survey are; four studies of diabetes disease, four studies of heart disease, three studies of breast cancer disease, and four studies of liver disease while we end the survey with Parkinson's disease patterns. The survey discussed the chosen papers from four axes: the dataset used, the model, the results and the limitations of the future works. Our perspective of using some techniques or not has been added implicitly. The total structure of the survey launched with an MLP explanation after that we present the literature review of the studies and at the end, the existing research with a conclusion added.

2 Multilayer perceptron artificial neural network (MLP-ANN)

It is one of the most important and most famous types of ANNs that were first discovered in the fifties of the last century but did not receive much attention. But with the discovery of backpropagation to train the ANN in the mid-eighties of the last century, great attention has been paid to it becoming one of the most popular technologies of our time [25]. MLP network is one of the types of feedforward networks of ANNs. The MLP network architecture consists of three main layers, an input layer, a hidden layer or (layers), and an output layer as shown in Figure 1 [34]. The hidden layer contains the neurons (nodes) that contain an activation function that determines the behavior of the node. The inputs pass to the first hidden layer via the input layer, where the number of nodes contained in the input layer must be equal to the number of input features [2]. Within the first hidden layer, the sum of each of the inputs with a given weight is calculated with the addition of the bias value according to the following equation [8]:

$$V = X1 * W1 + X2 * W2 + \ldots + Xn * Wn + Bias. \tag{2.1}$$

Within each node of the hidden layer, an activation function is used, which can be Sigmoid, RelU, etc., The activation function is used to determine the output from the node and pass it to the next layer. Then, the output is obtained using the output layer, which has an activation function that is selected according to the type of output required. This process is called forward feeding [34].

Based on the output, the error rate (the difference between the expected target and the target group) is calculated as the error rate should be minimized. Backpropagation is used to adjust MLP weights based on the error rate obtained in the previous epoch [8]. The MLP network is designed to solve problems that cannot be linearly separated. One of the most famous uses of the MLP algorithm are patterns recognition, as well as in predicting and diagnosing diseases [21]

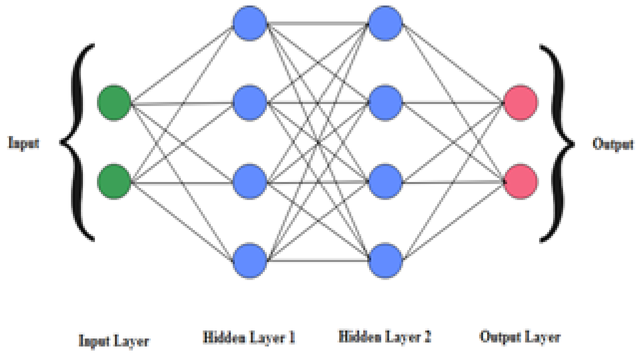

Figure 1: The Layer of MLP-ANN Network

3 Literature review

In recent years, the use of Artificial Neural Networks (ANNs) techniques has emerged in the field of pattern recognition in various fields. In this section, a set of studies addressing 5 types of common disease are summarized, all of them present a really threat and high death rate for human.

Diabetes is one of the most common diseases in the world that doctors find difficult to predict early. Mohapatra, et.al. [29] proposed to use one of the basic and most popular neural network models, the Multilayer Perceptron (MLP) network for early diabetes diagnosis. Performance experiments were performed on the PIMA Indian Diabetes data set containing 768 samples from Indian women where the proposed model achieved an accuracy of 77.5% for the diagnosis of diabetes.

Sivasankari, S. S., et al. [36]. Used well-tuned MLP technique to analyze diabetes data for early disease prediction by exploring hidden patterns in the PIMA Indian Diabetes dataset. The performance of the proposed model was compared with a group of other machine learning techniques (K-means, FCM, ANN, and CNN), where MLP technique achieved the best performance for early prediction of diabetes. To improve the accuracy of diabetes prediction Ranjeeth, S., and Venkata Ajay Krishna Kandimalla. [33] proposed a framework based on several stages which are data pre-processing, outlier detection and finally diabetes prediction. The radial basis function (RBF) network was used as an external detection model, then MLP) with optimal stochastic gradient descent (SGD) was used to predict diabetes more effectively. The proposed model achieved high accuracy with 96.9%, superior to each of the techniques (Naïve Bayes, SVM, Random Forest, Decision Tree, RFE, and MLP-SGD) used in the same study.

The fourth study of diabetes disease was proposed by Sushruta Mishra., et al [28]. Their project focused on optimizing the dataset, they assumed that the optimization algorithms can be applied to generate more reliable dataset symptoms that rise the accuracy. Their belief was correct by achieving 97.76% accuracy of employing multi-layer perceptron based on enhanced and adaptive genetic algorithm (EAGA).

According to statistics from the World Health Organization (WHO), heart disease is the highest cause of death in the world. So, Nahid Zaman, MD, et al [30]. Introduced a framework based on MLP and SVM technologies that explore clinical cardiology data sets to discover hidden patterns and predict heart disease. The presented system works in two stages. Stage I classifies only two classes of heart disease, while stage II classifies five classes of heart disease. Performance experiments were performed on the Cleveland heart disease dataset, which consists of 303 samples and 13 features. The proposed system achieved promising results when classifying two classes of heart diseases, while the prediction accuracy decreased when classifying 5 classes of heart diseases.

Djerioui, Mohamed, et al. [13] Compare two different ANNs, the MLP network and the long short-term memory (LSTM) network, for diagnosing heart disease. The aim of this study was to build an intelligent system for diagnosing heart disease. The performance of the two networks was tested on the Cleveland heart disease dataset from HCI, and the two networks achieved promising results in diagnosing heart disease.

Al Bataineh, Ali, and Sarah Manacek [3]. Tried to improve the MLP training process using particle swarm technique, which is one of the most popular optimization techniques. The proposed MLP-PSO hybrid technique was used to explore a data set of heart patients to distinguish between the presence of heart disease versus its absence. The performance of the hybrid MLP-PSO technique was compared with 10 different machine learning techniques, where the MLP-PSO technique achieved the best performance.

The last study of heart disease proposed by Deepika Db, Balaji N. [11], they adapted the enhanced by Brownian motion based on dragonfly algorithm with MLP to produce an efficient technique of heart disease predicting, in the same time an optimization algorithm was used to feature selection where the results were very promising with respect to state-of-the-art technique.

Al-Shargabi, Bassam, Feda Alshami, and Rami Alkhawaldeh. [4] proposed a well-tuned MLP system for diagnosing breast cancer, the most common type of cancer in women. Hyperparameters for MLP were set using the network search method to select the most suitable hyperparameters. Also, to improve the accuracy of the diagnosis, the feature selection technique was used to identify the most prominent features, as 4 features were selected out of 31 features for Wisconsin Diagnostic Breast Cancer (WDBC) dataset. The proposed system achieved a satisfactory performance outperforming the basic MLP technique.

Talatian Azad, Saeed, Gholam Reza Ahmadi, and Amin Rezaibana. [38] introduced a two-stage framework for a more accurate diagnosis of breast cancer in women. In the first stage, the hyperparameters of MLP technique were optimized using three different development techniques, namely GA, PSO (Particle Swarm Optimization), and ICA. Then in the second stage, the stacking method is used to build the ensemble model of MLP technique with hyperparameter optimization. Performance experiments were conducted on the WBCD dataset where the presented model yielded competitive results for breast cancer diagnosis.

ZAKIA SULTANA., et al. [37] employed one hidden layer of MLP model to obtain 91.32% accuracy of breast cancer classification. The number of dataset samples was 569 with 2 classes malignant 212 and benign 357 while the number of attributes for all dataset was ten.

Yuan-Xing Liu, et. al [24]. Proposed MLP model beside to six different models for earlier detection of Nonalcoholic fatty liver disease (NAFLD). The dataset reused from First Affiliated Hospital of Zhejiang University School of Medicine [9]. involved 15 315 Chinese case (10 373 training and 4942 testing sets) selected clinical and biochemical factors while the results evaluated according to several evaluation indicators. The MLP model is constructed by two hidden layers added to one input layer and one output layer. Although the low accuracy score achieved by MLP, which was 80.08% but, it appeared superior compared with other machine learning models. On the contrary of considerable research in the literature which shows the Body Mass Index (BMI) have no effect on the NAFLD, this study massively demonstrates the opposite idea, where the risk of fatty liver was found to be 3.55 times higher in overweight people than in normal participants, and 7.59 times higher in obese subjects. Eventually, there are several limitations in this study such as abdominal ultrasound served as the reference standard (better if used computer tomography (CT) more details). This study's inherent limitations include the fact that the accuracy and intra- / inter-rater reliability were not assessed and that some genetic variables that may be strongly related to the occurrence and progression of NAFLD were not considered.

Bilal Khan, et. al [22]. Applied MLP model for liver disease prediction, the dataset taken from UCI machine learning repository which have seven attributes first five of them deles with blood measures and others contain liver information. The model evaluated by three important measurements (mean absolute error (MAE), relative absolute error (RAE) and the accuracy). the MLP network combines several layers of knobs in a directed graph with each associated layer to the subsequent one excluding for the input knob, and every knob is a neuron with a non-linear simulation function.

Md. Sagar Hossen, et. al [20]. Tried to identify and detect the early stage of the liver disease DL, they used a MLP model with one input and one output layers and multi hidden layers with linear classifier where the output was either effective person or free. The dataset collected from 416 person which construct data table of 524 row and 10 columns. The result evaluated by different measurements among these factors the accuracy was 60.24 %. The must effected limitation is using classification method of machine learning variable integration, but it should use classifier with better efficient for deep learning to improve better prediction.

Rashid Naseem, et al. [32] used MLP model for early predictor of liver disease. The datasets were collected from UCI ML repository and Github, the first data involve 7 attributes with 345 samples and the second data involve 10 attributes with 583 samples. The MLP model obtained 71.58% accuracy with UCI dataset and 68.26% with the GitHub dataset.

M. Uday Kumar1, et al. [23] proposed 8-layer MLP model to predict the Parkinson's, the authors used ensemble methods to obtain 97.02% of accuracy detection. Momentum technique modulated with the model and high batch size was used.

Here, Nalini Chintalapudi, et al. [10] use MLP model with 32 dense layers for determine Parkinson's or not from 54 samples of recorded voices collected form UCI machine learning repository with 96.93 accuracy.

Sarfaraz Masood, et al. [26] the authors aimed to detect the Parkinson's disease (PD) from voice analysis, they focused on explore the correlation among the various observation in the PD voice recorded samples [35]. A new feature selection method called two-stage ensemble-based was proposed. After selected the most effected features a fine-tuning MLP model was prepared to receive these features as inputs while K-fold cross-validation used as resampling strategy. The model achieved 100% accuracy beside other measurements.

Ghayth AlMahadin, et al. [6] this study based-on increases the model accuracy using blende of single processing and resampling technique, the result integrated with combination of MLP and Borderline SMOTE. Wearable devices were used to collect data, where the subjects wore smartwatch, Samsung smart phones and GENEActiv accelerometer while the tasks based on movement exercises [1]. The approach model obtains 93.81% overall accuracy through the experiments.

Table 1: Summarize the studies of literature review

Re.	problem	Dataset and Year	Technique	MLP Evaluation	Objective	Limitation
[18]	Diabetes	PIMA 2019	MLP	77.50% Ac.	Diabetic or not	The achieved accuracy is not good enough.
[19]	Diabetes	PIMA 2022	MLP, K-means, FCM, ANN, and CNN	86.08% Ac.	Diabetic or not	The achieved accuracy is not good enough.
[20]	Diabetes	PIMA 2020	Naïve Bayes (NB), SVM, Random Forest (RF), Decision Tree (DT), RFE, MLP-SGD and RFE + MLP-SGD	96.9% Ac.	Diabetic or not	The model is a bit complicated.
[21]	diabetes	PIMA-INDIA 2020	MLP+GA	97.76%	presence of diabetes on the basis of symptoms	The model classifiy only femal patient, number of sampls is small and genration number need to be larger
[22]	Heart Disease	Cleveland 2019	MLP, and SVM	90.57% Ac.	Classification of five classes of heart disease	The achieved accuracy is not good enough when classified multi classes of heart disease
[23]	Heart Disease	Cleveland 2020	MLP, and LSTM	94.73% Ac.	Heart disease or not	The number of samples for the data set is limited
[24]	Heart Disease	Cleveland 2022	MLP-PSO, RF, DT, Extra Trees, NB, Gradient Boosting, KNN, Logistic Regression (LR), MLP, XGB, and SVM	84.60% Ac.	Heart disease or not	The achieved accuracy is not good enough.

[25]	Heart disease	www.kaggle.com/ronitf/heart-disease-uci 2022	MLP+EBMDA	94.28%	Prediction as normal and ubnoraml	Very small dataset sampls 305 and 14 attributs, using dragonfly algorithm
[26]	Breast Cancer	WDBC 2019	MLP+ Grid search	97.19% Ac.	Breast cancer or not	The number of samples for the data set is limited
[27]	Breast Cancer	WDBC 2021	MLP+ Ensemble method	98.74% Ac.	Breast cancer or not	The number of samples for the data set is limited
[28]	Breast cancer	UCI Irvine machine learning repository 2021	MLP	91.32%	malignant or benign	no Pre-processing was used
[29]	liver	First Affiliated Hospital of Zhejiang University School of Medicine 2021	MLP	79.3% Ac.	Earlier identification of the NAFLD disease.	Several limitations such as reliability on abdominal ultrasound, various genetic factors were not included, and intra-/inter-rater reliability were not evaluated.
[31]	liver	UCI Machine Learning Repository 2019	MLP	71.60% Ac.	Earlier finding for liver disease.	The number of samples used is exceedingly small 356 and six attributes, which negatively on the results.
[32]	liver	The dataset is collected from UCI Machine Learning Repository 2022	MLP	60.24% Ac.	Early stagy and identification risk factor of liver disease.	Exceedingly small samples number 583 with 10 attributes. Using liner classifier with deep learning model.
[33]	Liver	First data UCI ML repository, second data Github	MLP	First data 71.58% , second data 68.26% Ac.	Early detection of liver	Unbalanced dataset, poor MLP model, no Preprocessing algorithms were applied
[34]	Parkinson	-	MLP + ensemble method	97.02% Ac.	Prediction	The system lacks to fine tuning design

[35]	Parkinson	UCI machine learning repository	MLP + SMOTE	96.93% Ac.	Detection	Low subjects samples and lake with lables
[36]	parkinson	SAKA 2021	MLP+K-fold	100% Ac.	Early detection parkinson or non-parkinson	-
[38]	Parkinsons	taken from Levodopa response trial wearable data	MLP+ Borderline +SMOTE	93.81% Ac.	Five graid severity parkinson disease classes classification	Small dataset, the data generated in single environment, the approach should test on more than one dataset.

4 Discussion

In this section, the studies mentioned in Table 1 are discussed. During the analysis of studies that dealt with the use of the MLP network to explore the hidden patterns of the diabetes dataset, it was observed that the performance of the model individually was not good enough. This can be explained by the lack of sufficient data to train the MLP network as in the study [29]. However, in the study [36], the performance of the MLP model was improved to achieve an accuracy of 86.08% by fine-tuning the model parameters. While the accuracy of diabetes diagnosis can be significantly improved when MLP technology is combined with SGD techniques, it achieves a classification accuracy of 96.9% [33]. The [A1] thougt differently by employing the genetic algorithm GA to optimize the dataset before feeding them to the model, attribute selection task was used by open-scourse java framework called (WEKA.attributeSelection.GeneticSearch) this technique genrate new solutions represents by 0's and 1's for each sample where finally the 0's attributes will be drobed. By using GA, a totaly new dataset genrated which are pass to the simple MLP model that achieved high accuracy comperd with the preivous methods. The [28] method demonstrate that solving the dataset issues is more importent than orginaze and arrange the MLP model.

In the study [30], it was observed SVM technique and MLP network achieved competitive results when used to classify whether a person had heart disease or not. While the performance of the two methods was observed to decrease when they were used to classify five diverse types of heart disease. Also, in study [13] both the LSTM network and the MLP network achieved competitive outcomes for binary diagnosis of heart disease. In the study [3], the MLP network was integrated with the PSO optimization algorithm to improve the accuracy of heart disease diagnosis, but the improvement was not significant enough. The last study combain the dragonfly algorithm DA with MLP [11] see Table 1. Although of achieving 94.28% accuracy with very small dataset but using DA represent a limitation itself. DA has problem in the both exploitation and exploration phases. The team is credited with improving the exploration phase of DA but, the raw algorithm has weakness in exploit phase it is always miss target.

In both studies [4, 38] the MLP network achieved promising results for diagnosing breast cancer in women. The performance of automatic adjustment of the MLP network hyperparameters using optimization algorithms to obtain a good diagnosis accuracy for breast cancer, where the study [4] achieved a diagnosis accuracy of 97.19%, while the study [38] achieved a diagnosis accuracy of 98.74%. In the last study [37] 569 sample were used to early detection of breast cancer if it malignant or benign, the model used contain just one hidden layer while the pre-processing steps was already done form dataset scourse. The accuracy obtined 91.32% which cocider weak with respect to the prior results. In order to increase the accuracy the model should use the pre-prosessing methods also more complex model with fine tuning parameters can be useful and imporved the performance positively.

By looking at the liver disease problem which illustrats four different datasets and models as well [24, 22, 20, 32], we can notice the low results achieved compared with the results obtained in the prior pattrens (for the sake of approximation, not comparison per se) see Table 1. The reason lies behind using the MLP model solo without improving or hybridization also unappling the pre-processing technique like data balancing, resampling methods or feature selection algorithms. All the above patterns used at least one method or algorithm to improve the performance of MLP. Despite the superior design of the model there are some results that were disappointing, it may come to the reader's mind the model or the technique used is useless such as in the last study of liver disease were achieved 60.24% accuracy. The performance of any model significantly depends on the dataset used. Sometimes the dataset is not appropriate with the designed model or it is not preprocessed well, all these aspects should be reviewed before judge on the performance of the model.

Last part of this section we discussed the Parkinson's disease pattern. By returning to the Table 1 we can note the high results achieved by chosen studies for this disease. The reason lies in the nature of the disease, as Parkinson's disease is known as nerve damage that usually affects the elderly resulting in involuntary vibrating movements in the limbs, head, or even certain parts of the patient's body. Thus, the motor symptoms are truly clear and can be diagnosed easily see [23, 26], except for voice diagnosis of the disease see [10] or determining the degree of the disease such as [6]. Because of low dataset in both cases the models have no chance to training well, we can solve this issue by collect data from muli-sources and pre-processing them to create appropriate data or using transfer learning method by that all data will be for testing and there is no need to share them with training phase.

5 Occlusion and future work

In this survey we summarized 5 patterns of healthcare recognition; diabetes, heart disease, breast cancer, liver disease and Parkinson's disease. Each of them branched into several datasets as a result we obtained of a modern integrated study that includes 19 articles. Recent studies and hot topics have been chosen. Moreover, we reviewed higher impact factors journals such as Elsevier, Sprenger and IEEE (Institute of Electrical and Electronics Engineers) as well as few other journals. The paper is surveying the healthcare patterns in an investigative way, where it detailed each research from four aspects: dataset used, MLP models structures, results, and limitations. The selected studies ware miscellaneous and Inclusive involved variant datasets even for the same type of pattern as well as the models were used solo or adaptive with other technologies and methods. We started our search with a wealthy information introduction that took on the importance of healthcare pattern recognition subject to give the reader an adequate perception of the importance of the topic, followed by a preface to the field of artificial intelligence then entered to the core of the topic to end with the research sections. The second period involved explanation of the MLP with massive concepts of ANNs structures and backpropagation, this period followed by the core of our survey where significant literature has been reviewed with aggregated table. Eventually, the discussion and conclusion sections supported with the future work have finished the research.

As futures directions, there are several procedures suggested to be followed to improve the performance of healthcare pattern recognition systems: One of these suggestions is training the MLP model with huge datasets to improve the model's performance. Imbedding optimization algorithms to fine tune hyperparameters rather than manually tuning to increase the quality of the model. Third suggestion is integrating MLP technique with other ML techniques such as random forest. Also, it can build ensemble method of MLP using bagging or boosting methods.

On the private level, we aspire in the future to add all the remaining patterns related to the field of healthcare and increase the ways of discussing them for the purpose of collecting all previous studies to be a comprehensive reference for all researchers in this field.

References

[1] *Datasets | Parkinson's Disease, https://www.michaeljfox.org/data-sets.*

[2] S. Abirami and P. Chitra, *Energy-efficient edge based real-time healthcare support system*, Adv. Comput., vol. 117, Elsevier, 2020, pp. 339–368.

[3] A. Al Bataineh and S. Manacek, *MLP-PSO hybrid algorithm for heart disease prediction*, J. Person. Med. **12** (2022), no. 8, 1208.

[4] B. Al-Shargabi, F. Alshami, and R. Alkhawaldeh, *Enhancing multi-layer perception for breast cancer prediction*, October 2019.

[5] M.F. Alghifari, T.S. Gunawan, and M. Kartiwi, *Speech emotion recognition using deep feedforward neural network*, Indones. J. Electric. Engin. Comput. Sci. **10** (2018), no. 2, 554–561.

[6] G. AlMahadin, A. Lotfi, M.M. Carthy, and P. Breedon, *Enhanced parkinson's disease tremor severity classification by combining signal processing with resampling techniques*, SN Comput. Sci. **3** (2021), no. 1, 63.

[7] Y.Y.M. Aung, D. Wong, and D.S.W. Ting, *The promise of artificial intelligence: a review of the opportunities and challenges of artificial intelligence in healthcare.*, Br. Med. Bull. **139** (2021), no. 1.

[8] E. Bisong, *Building machine learning and deep learning models on Google cloud platform*, Springer, 2019.

[9] C. Cen, W. Wang, S. Yu, X. Tang, J. Liu, Y. Liu, L. Zhou, J. Yu, and S. Zheng, *Development and validation of a clinical and laboratory-based nomogram to predict nonalcoholic fatty liver disease*, Hepatology Int. **14** (2020), no. 5, 808–816.

[10] N. Chintalapudi, G. Battineni, M.A. Hossain, and F. Amenta, *Cascaded deep learning frameworks in contribution to the detection of parkinson's disease*, Bioengineering **9** (2022), no. 3, 116.

[11] D. Deepika and N. Balaji, *Effective heart disease prediction using novel MLP-EBMDA approach*, Biomed. Signal Process. Control **72** (2022), 103318.

[12] S. Dick, *Artificial intelligence*, (2019), Publisher: PubPub.

[13] M. Djerioui, Y. Brik, M. Ladjal, and B. Attallah, *Heart disease prediction using MLP and LSTM models*, IEEE, 2020, pp. 1–5.

[14] M.A. Fauzi, *Random forest approach fo sentiment analysis in Indonesian*, Indones. J. Electric. Engin. Comput. Sci. **12** (2018), no. 1, 46–50.

[15] M.A. Fauzi, A.Z. Arifin, S.C. Gosaria, and I.S. Prabowo, *Indonesian news classification using Naïve Bayes and two-phase feature selection model*, Indones. J. Electric. Engin. Comput. Sci. **2** (2016), no. 3, 401–408.

[16] M.A. Fauzi and A. Yuniarti, *Ensemble method for indonesian twitter hate speech detection*, Indones. J. Electric. Engin. Comput. Sci. **11** (2018), no. 1, 294–299.

[17] E. García, R. Peñabaena-Niebles, M. Jubiz-Diaz, and A. Perez-Tafur, *Concurrent control chart pattern recognition: A systematic review*, Mathematics **10** (2022), no. 6, 934, Publisher: MDPI.

[18] T.S. Gunawan, A. Noor, and M. Kartiwi, *Development of english handwritten recognition using deep neural network*, Indones. J. Electric. Engin. Comput. Sci. **10** (2018), no. 2, 562–568.

[19] J. Han, J. Pei, and H. Tong, *Data mining: concepts and techniques*, Morgan Kaufmann, 2022.

[20] M.S. Hossen, I. Haque, P.R. Sarkar, M.A. Islam, W.A. Fahim, and T. Khatun, *Examining the risk factors of liver disease: A machine learning approach*, 2022 7th International Conference on Communication and Electronics Systems (ICCES), June 2022, pp. 1249–1257.

[21] S. Javaid and N. Saeed, *Neural networks for infectious diseases detection: Prospects and challenges*, (2021), Publisher: TechRxiv.

[22] B. Khan, R. Naseem, M. Ali, M. Arshad, and N. Shinwari, *Machine learning approaches for liver disease diagnosing*, Int. J. Data Sci. Adv. Anal. **1** (2019), no. 1, 27–31.

[23] M.U. Kumar, S.R. Kumar, and S.S. Kumar, *Cross validated hard ensemble mlp classification technique to detect*, J. Compos. Theory.

[24] Y. Liu, X. Liu, X. Cen, C.and Li, J.-M. Liu, Z.-Y. Ming, S.-F. Yu, X.-F. Tang, L. Zhou, J. Yu, K.-J. Huang, and S.-S. Zheng, *Comparison and development of advanced machine learning tools to predict nonalcoholic fatty liver disease: An extended study*, Hepatobil. Pancreatic Diseases Int. **20** (2021), no. 5, 409–415.

[25] B. Macukow, *Neural networks–state of art, brief history, basic models and architecture*, Springer, 2016, pp. 3–14.

[26] S. Masood, K.W. Maqsood, O. Pal, and C. Kumar, *An ensemble-based feature selection framework for early detection of parkinson's disease based on feature correlation analysis*, Math. Meth. Appl. Sci. (2021) (en).

[27] P. Melin, V. Herrera, D. Romero, F. Valdez, and O. Castillo, *Genetic optimization of neural networks for person recognition based on the Iris*, Telkomnika **10** (2012), no. 2, 309.

[28] S. Mishra, H.K. Tripathy, P.K. Mallick, A.K. Bhoi, and P. Barsocchi, *EAGA-MLP—an enhanced and adaptive hybrid classification model for diabetes diagnosis*, Sensors **20** (2020), no. 14, 4036.

[29] S.K. Mohapatra, J.K. Swain, and M.N. Mohanty, *Detection of diabetes using multilayer perceptron*, Springer, 2019, pp. 109–116.

[30] M. Nahiduzzaman, M.J. Nayeem, M.T. Ahmed, and M.S.U. Zaman, *Prediction of heart disease using multi-layer perceptron neural network and support vector machine*, IEEE, 2019, pp. 1–6.

[31] T. Nakaura, T. Higaki, K. Awai, O. Ikeda, and Y. Yamashita, *A primer for understanding radiology articles about machine learning and deep learning*, Diagn. Intervent. Imag. **101** (2020), no. 12, 765–770.

[32] R. Naseem, B. Khan, M.A. Shah, K. Wakil, A. Khan, W. Alosaimi, M.I. Uddin, and B. Alouffi, *Performance assessment of classification algorithms on early detection of liver syndrome*, J. Healthcare Engin. **2020** (2020), e6680002.

[33] S. Ranjeeth and V.A.K. Kandimalla, *Predicting diabetes using outlier detection and multilayer perceptron with optimal stochastic gradient descent*, IEEE, 2020, pp. 51–56.

[34] Q. Saihood and E. Sonuç, *The efficiency of classification techniques in predicting anemia among children: A comparative study*, Springer, 2022, pp. 167–181.

[35] B.E. Sakar, M.E. Isenkul, C.O. Sakar, A. Sertbas, F. Gurgen, S. Delil, H. Apaydin, and O. Kursun, *Collection and analysis of a parkinson speech dataset with multiple types of sound recordings*, IEEE J. Biomed. Health Inf. **17** (2013), no. 4, 828–834.

[36] S.S. Sivasankari, J. Surendiran, N. Yuvaraj, M. Ramkumar, C.N. Ravi, and R.G. Vidhya, *Classification of diabetes using multilayer perceptron*, IEEE, 2022, pp. 1–5.

[37] Z. Sultana, M.A. Khan, and N. Jahan, *Early breast cancer detection utilizing artificial neural network*, WSEAS Trans. Bio. Biomed. **18** (2021), 32–42.

[38] S. Talatian Azad, G. Ahmadi, and A. Rezaeipanah, *An intelligent ensemble classification method based on multi-layer perceptron neural network and evolutionary algorithms for breast cancer diagnosis*, J. Exper. Theor. Artif. Intell. (2021), no. 0, 1–21.

[39] P. Zheng and L. Ni, *Smart phone and next generation mobile computing*, Elsevier, 2010.