AN INTELLIGENT SYSTEM BASED ON DEEP LEARNING TO AID IN MEDICAL DIAGNOSIS IS CALLED HEALTH SEARCH

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Abstract

One of the time-consuming and challenging tasks that healthcare professionals must regularly complete is medical diagnosis. An accurate and timely examination of each patient is crucial to establishing an effective treatment plan. This evaluation procedure can occasionally take a long time due to the quantity of tests that need to be done, which can have a detrimental impact on the patient's recovery. The goal of this work is the creation of new software that, using artificial intelligence (AI), aids medical professionals in helping patients be diagnosed and in reducing the likelihood that they will contract a particular disease. This software will be developed using test data analytics and readily available demographic data. The system enables the storage of several Deep Learning (DL) models that have been previously developed for the diagnosis of various illnesses. Based on the available medical data, these models provide predictions. One of these models has been successfully evaluated in the use case of stroke event diagnosis.

Keywords: Deep learning, artificial intelligence, stroke, and intelligence systems

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1. Introduction

One of the main duties of doctors is making a diagnosis, which is therefore the first step in providing appropriate care. The diagnosis is based on the study of trustworthy data, and the results can only be legitimate if they are founded on clear ideas and precise information. A number of fundamental assumptions or ideas underpin the diagnostic procedure (Díaz Novás et al., 2006):

- Relationship between doctor and patient: vital to getting the data the doctor needs. It may be feasible to offer the patient comfort and security if this relationship is appropriate.
- Anamnesis: Between 50% and 75% of diagnoses are based on the responses to questions.
- Physical examination: Complements anamnesis because physical symptoms are verifiable, objective illness markers that serve as reliable, unfalsifiable facts.
- Association of symptoms and signs: While making a diagnosis, clinicians frequently attempt to group symptoms and indicators.

The completion of many medical tests, including blood tests, X-rays, cardiograms, MRIs, etc., is often required for this process. These procedures can be time-consuming, but they are occasionally essential to the patient's proper rehabilitation.

These days, there are a tonne of potential applications due to the massive quantity of data created daily, the computational power of new technology, the growth and spread of AI, and so on. One of the fields where these advancements may be implemented with positive outcomes is medicine.

Artificial Neural Networks (ANN) are a paradigm for machine learning and data processing that are based on how the human nervous system functions. A group of neurons are connected via connections to form an ANN. Each neuron receives as inputs the outputs of the neurons in the layers above it, multiplies these inputs by a weight, adds the partial results, and then determines its output using an activation function. Its output serves as the precursor neuron's input in turn.

The ANN is made up of all of these linked neurons together. In this view, ANN are just massively interconnected parallel networks of basic and hierarchically arranged pieces that attempt to interact with real-world objects in a manner similar to the organic nervous system. To find the best network design for a particular task, these approaches rely on accurate models and training examples rather than explicit theory (Goodfellow et al., 2017).

The primary goal of this study is to create a software system that can be utilised by any medical facility as a support tool in the maintenance of patient data and the process of medical diagnosis. In order to achieve this goal, the created system enables the storage of several DL-based models that have been previously trained for the diagnosis of various diseases and enable predictions from the available medical data.

An ANN has been created and trained for the prediction of stroke disease in order to develop the system's architecture and assess the accuracy of its operation. The World Health Organization (WHO) reports that stroke incidents account for around 11% of all fatalities worldwide and are the second highest cause of mortality. Blood tests, brain imaging (CT, MRI, and X-ray), ECG and EEG, as well as other physiological neurological techniques like Induced Potential Tests, are frequently used to diagnose stroke illness (Lee, 2002).

The remainder of the study is structured as follows: in Section 2, we explore a few additional studies involving the use of AI to analyse medical data. The architecture of the created system as well as the Neural Network model training are then both explained in Section 3. After that, in Section 4, we present the findings of the tool's evaluation following a test period. Part 5 concludes by summarising the findings and future study.

2. Literature survey

Here is a list of earlier studies that use ANN and Expert Systems (ES) to tackle the challenge of establishing a diagnosis. They are all concentrated on the management of particular disorders.

Two Multilayer Perceptrons (MP) were trained in (See & Yeung, 2019) to classify various forms of dementia and map them to the MMSE score using regional CortexID Z-scores. Comparing the suggested architecture's classification accuracy to medical diagnoses made using both clinical and laboratory data, it shows good results.

In (Ghwanmeh et al., 2013) a different ANN-based approach is given. The technique enables the diagnosis of ventricular septal defect, mitral stenosis, and aortic stenosis, the three major heart conditions. Also, it can help physicians use actual medical data to establish advanced cardiac diagnoses.

In order to aid physicians in the treatment of staph infectious disorders, authors of (Uka et al., 2020) devised an ES for fast identification and detection of Staphylococcus Aureus germs on human skin. Using the created user interface, the system's inference engine responds to the physicians' requests.

An ANN is used in the experiment described in (Liao, 2020) to create a binary classification system that determines whether or not the subject of the study has Parkinson disease. A classification success rate of about 80% is attained by the classifier using 16 biological quantities.

In (Bijar & Mahdavifar, 2011), scientists described a unique method for segmenting multiple sclerosis lesions from brain tissues using Markov random fields and an Expectation Maximization (EM) algorithm that is entropy-based. The suggested method outperforms earlier approaches in the field by estimating a gaussian mixture model with three kernels: cerebrospinal fluid (CSF), healthy tissue, and multiple sclerosis lesions.

Momentum Contrast (MoCo) is an AI-based initiative that leverages clinical information from chest X-rays to help researchers and doctors identify which patients are most at risk for COVID-19-related deterioration.

Several ANN-based research have examined the issue of identifying the potential for experiencing a stroke episode in recent years. In (Sriram et al., 2021), Chin et al. used data augmentation to increase the frequency of patch pictures in CT scans of patients who had ischemic strokes. They then used these patch images as input to CNN models to diagnose ischemic stroke with high accuracy. A Res-CNN model that automatically identified acute ischemic stroke in MRIs was proposed by authors in (Chin et al., 2017). The Res-CNN model used the residual unit to resolve the performance deterioration issue.

Convolutional Neural Networks (CNN) were used by (Sainath et al., 2013) to offer a framework for the classification of stroke using CT images in order to distinguish between a healthy brain and either an ischemic stroke or a hemorrhagic stroke. According to the Transfer Learning theory, CNN was very accurate when coupled with other consolidated machine learning techniques, such as the Bayesian Classifier, Multilayer Perceptron, k-Nearest Neighbor, Random Forest, and Support Vector Machines.

Authors have suggested a strategy in (Serj et al., 2018) to predict stroke disease using DL models on unprocessed EEG data. The model was trained using multiple neural architectures, including LSTM, using data gathered from real-time electroencephalography (EEG) sensors. Our method relies solely on laboratory biological quantities collected from patient analytics and clinical data rather than graphical information. The system created in this research, in contrast to the studies given above, enables the storing of several ANN-based models to assist in the diagnosis of different illnesses, which is, in our opinion, a key improvement over existing system. Even some of the neural network-based models that employ numerical or categorical variables as input data from laboratory tests or clinical and/or demographic information of the patient might be used with the system. The created system is described in the following parts.

3. Detailed system description

The architecture of Health Seek and the creation of each of its four components—a multi-platform mobile app, an ANN for the prediction of cerebrovascular infarcts, a database that houses models and all patient medical data, and an API that serves as a connecting thread between them all—are both covered in this section.

An ANN-based model that estimates the likelihood that a particular patient will experience a stroke event from a collection of known biological parameters at a certain instant has been constructed and trained for the creation of the system's first functioning prototype.

The data is requested by the mobile application, and the API collects this information to execute the request later. For instance, the API will respond as follows to a doctor's request for a patient's statistics:

- The app request is gathered and dealt with.
- To get all illnesses listed in the database, a query is created and run.
- The model for each illness is then imported from the database, and the patient's information is gathered in accordance with the features that each model requires.
- The forecast is made using the recorded data by the ANN.
- The user may then view the findings by returning to the app's UI.

After the discussion of the various system components, Figure 1 illustrates graphically how these components relate to one another.

3.1. An applied neural network architecture

Using Python, a high-level, object-oriented, and interpreted programming language, the neural network has been developed. The fact that Python's standard library and interpreter are both publicly available and that there are other libraries that make it easier to create neural network topologies, such Pytorch or TensorFlow, is one of its most significant advantages. TensorFlow has been utilised for this particular project under the Keras high-level framework, which makes the creation of applications of this kind quick and simple.

An ANN to determine if a patient is likely to get a stroke has been created and trained using a dataset (Rawat & Wang, 2017) made up of 4996 patients with the features shown in Figure 2 for the system's creation and assessment. The dataset gathers data on demographic and laboratory analytical information for patients in attempt to forecast the likelihood of having a cerebral stroke using several criteria, including smoking status, age, gender, and past medical conditions. With additional ANN-based models for different illnesses that have been previously trained and saved in the application database, the system is simply scaleable.

The development of a model that enables generating probabilistic predictions about whether certain patients will experience a brain stroke is the major goal of utilising an ANN. A Multi-Layer Perceptron (MLP) has been utilised as a binary classifier to do this after being trained. Several designs and combinations of input variables have been explored to increase the accuracy of the findings.

As the dataset had multiple records with null values for various features, such the "bml" feature, it was required to do a cleaning and data preparation operation before to training. For the "bml" feature, the average value of the remaining non-null records was utilised as the value.

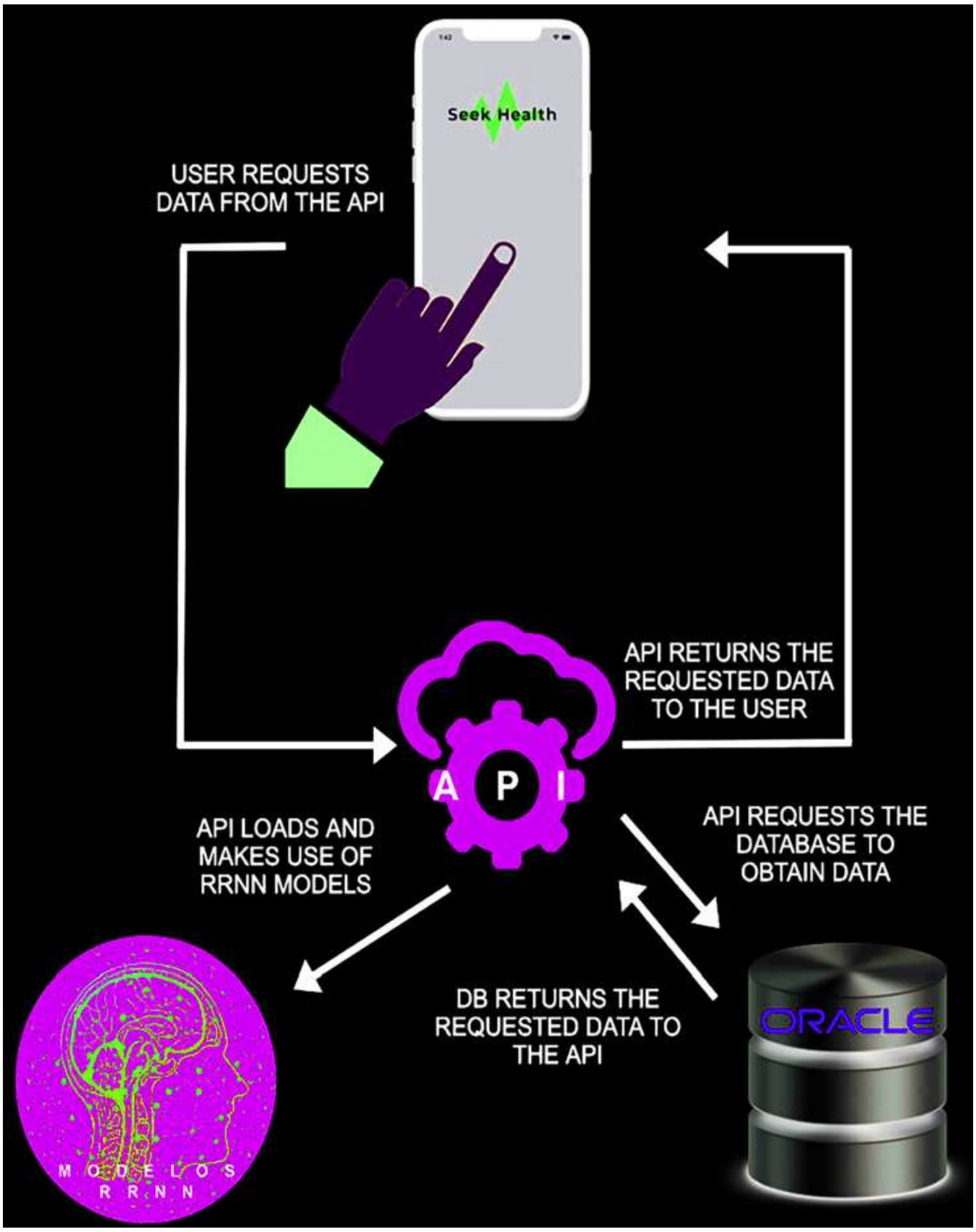

Figure 1: Infrastructure system seeks health

Attribute information

1) Id: unique identifier
2) gender: "Male", "Female" or "Other"
3) age: age of the patient
4) hypertension: 0 if the patient doesn´t have hypertension, 1 if the patient has hypertension
5) heart_disease: 0 if the patient doesn´t have any heart disease, 1 if the patient has a heart disease
6) ever_married: "No" or "Yes"
7) work_type: "children", "Govt_job", "Never_worked", "Private" or "Self-employed"
8) Residence_type: "Rural" or "Urban"
9) avg_glucose_level: average glucose level in blood
10) bmI: body mass index
11) smoking_status: "formerly smoked", "never smoked", "smokes" or "Unknown"
12) stroke: 1 if the patient had a stroke or 0 if not

*Note: "Unknown" in smoking_status means that the information is unavailable for this patient

Figure 2: A listing of the features of the model

There was also a serious issue with imbalanced data that has to be fixed. Figure 3 illustrates the issue of imbalanced data, where the proportion of cases without disease (Stroke = 0) is significantly larger than the proportion of cases with disease (Stroke = 1). Due to this aspect, the model's performance was insufficient, leading to overfitting. In order to address this issue, a fresh sample of 350 records with zero strokes and 249 records with a value of one was obtained (Rakhlin et al., 2018).

The dataset was divided into test, validation, and train subsets once the data cleaning phase was finished. A examination of the practical elements that boosted prediction performance came next. A Correlation Matrix (Islam et al., 2018), which displays the correlations between pairs of variables for a particular patient in the dataset, was utilised for this. The dataset contained some category characteristics that needed to be adjusted, as seen in Figure 4, but this approach demands that all of the features be numeric. There are several methods for translating category variables to numeric values:

- As with the "sex" variable, change the original variable to a binary one with just two possible values.
- To create a list of integers, each one representing a different category, dummify the variable.
- Assign a distinct number to each available category.

Features like "sex" and "ever married" that have two potential values were transformed into binary variables. The remaining category characteristics were hazy. Although this isn't always the case, dummifying a variable typically yields superior outcomes in the behaviour of the neural network. The correlation matrix was computed once all the characteristics had been corrected. The dataset's correlation matrix is displayed in Figure 5.

The correlation matrix shows that the characteristics "sex," "hypertension," "heart disease," "avg glucose level," and "ever married" appeared to be more connected to the target variable.

The optimum ANN architecture for the data was then constructed. A variety of experiments testing various architectures have been conducted in the past, including the addition and/or deletion of layers, alterations to the number of neurons in each layer, the addition of dropout, modifications to the activation function, adjustments to the learning rate, and the addition and deletion of various features. Using this procedure, the ideal network architecture for the particular issue was developed. Figure 6 displays the outcomes of training using the characteristics selected from the correlation matrix.

There were several characteristics that just added noise to the model, it was discovered after multiple testing. The Principal Component Analysis (PCA) technique (Liu et al., 2020) was used to overcome this issue, and it was discovered that employing just five characteristics produced the greatest results. Lastly, Table 1 displays the most important features that improve the model's performance. The complete network design is then presented in Table 2. Figure 7 displays the model accuracy and model loss following the training procedure using the model's designated architecture.

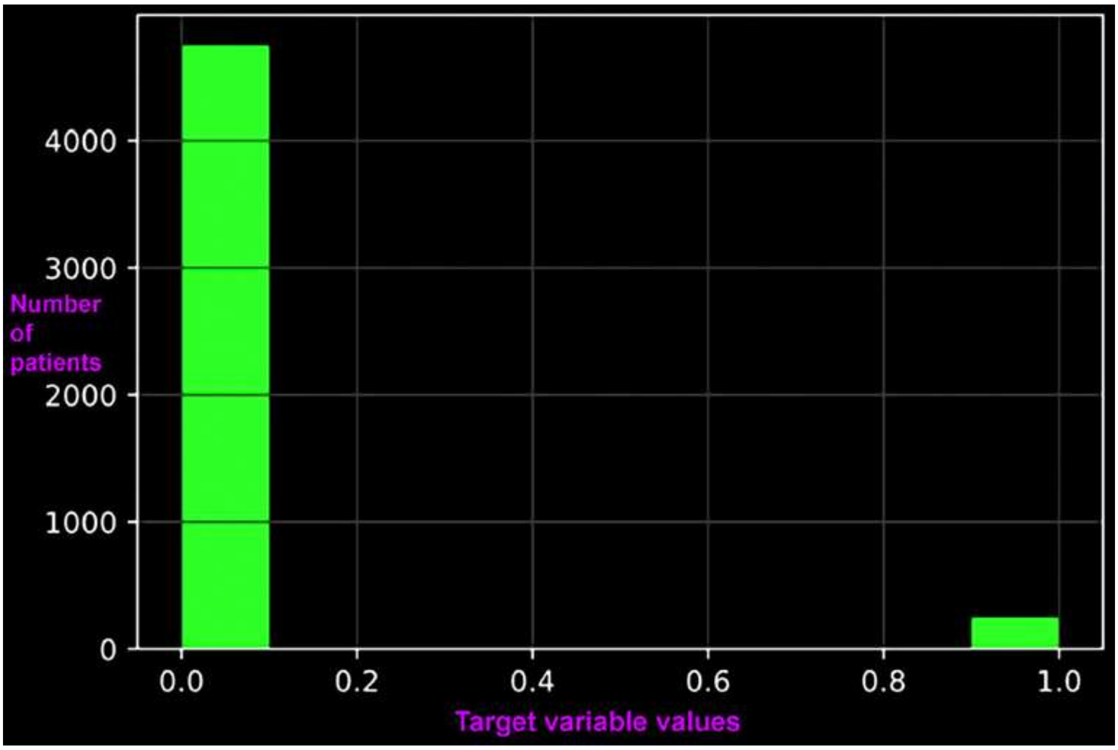

Figure 3: Initially, the target variable's distribution (stroke)

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1

Figure 4: Dataset structure taking the characteristics into account

	sex	age	hypertension	heart_disease	ever_married	avg_glucose_level	stroke	work_type_Cuenta propia	work_type_F
sex	1.000000	0.057112	-0.009366	0.141582	0.073601	0.119851	0.052152	-0.062259	
age	0.057112	1.000000	0.285346	0.280065	0.574830	0.283928	0.542299	0.291432	
hypertension	-0.009366	0.285346	1.000000	0.061913	0.093616	0.172973	0.247019	0.170978	
heart_disease	0.141582	0.280065	0.061913	1.000000	0.093368	0.255815	0.259166	0.009695	
ever_married	0.073601	0.574830	0.093616	0.093368	1.000000	0.195714	0.231581	0.159786	
avg_glucose_level	0.119851	0.283928	0.172973	0.255815	0.195714	1.000000	0.282338	-0.001767	
stroke	0.052152	0.542299	0.247019	0.259166	0.231581	0.282338	1.000000	0.142732	
work_type_Cuenta propia	-0.062259	0.291432	0.170978	0.009695	0.159786	-0.001767	0.142732	1.000000	
work_type_Funcionario	-0.039776	0.095166	0.043436	-0.016665	0.093353	0.020359	-0.032120	-0.194832	
work_type_Nunca	0.004854	-0.557086	-0.120885	-0.094924	-0.501161	-0.099051	-0.198984	-0.136184	
work_type_Privado	0.075779	-0.015779	-0.107144	0.052632	0.064105	0.038593	0.008356	-0.612106	
residence_type_Rural	0.081513	0.009868	0.030888	-0.015924	0.057724	0.018900	-0.057837	0.046992	
residence_type_Urbano	-0.081513	-0.009868	-0.030888	0.015924	-0.057724	-0.018900	0.057837	-0.046992	
moking_status_Desconocido	0.034918	-0.301477	-0.190415	-0.045320	-0.207181	-0.096719	-0.119200	-0.118877	
smoking_status_Nunca	-0.124038	0.097453	0.117743	-0.092034	0.022470	-0.004314	-0.020314	0.072328	
smoking_status_fuma	0.084146	-0.005772	0.034349	0.106201	0.103767	0.035243	-0.011193	-0.022524	
smoking_status_fumaba	0.032985	0.212842	0.030452	0.059987	0.184664	0.076304	0.163853	0.062010	

Figure 5: following pre-processing the dataset, the correlation matrix

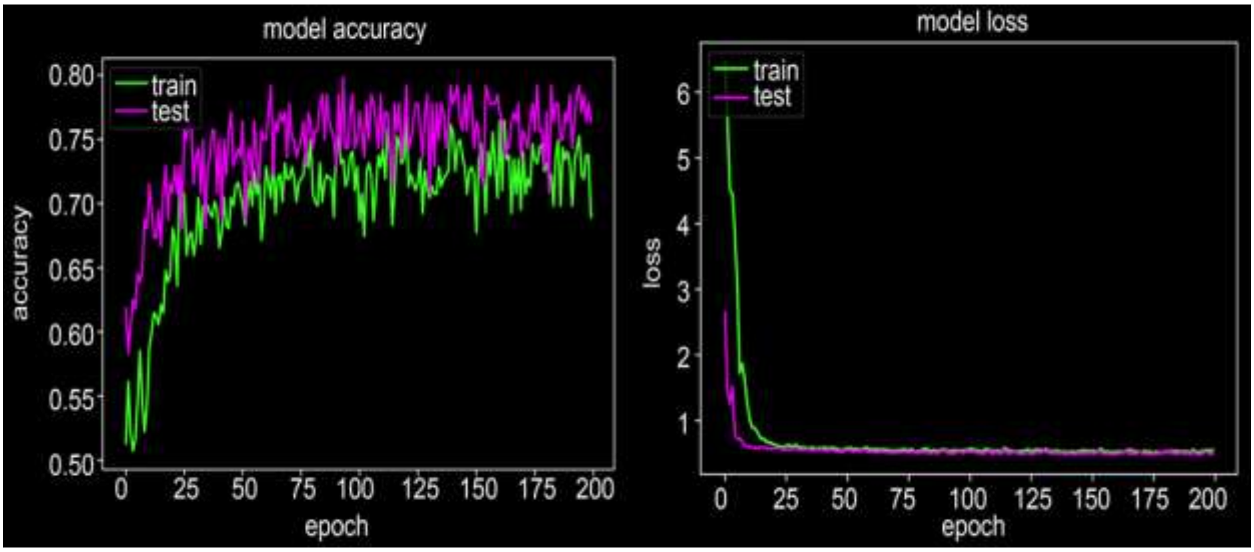

Figure 6: Outcomes of training using the correlation matrix's selected features

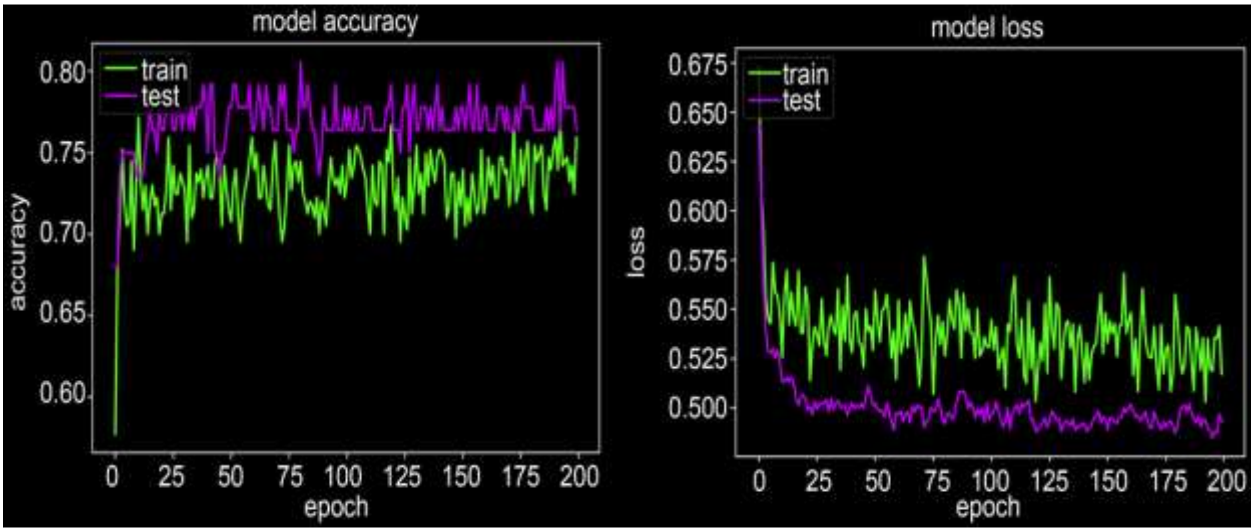

Figure 7: For the final architecture, model accuracy and loss

Table 1: Most significant qualities

Features providing best results
sex
age
hypertension
heart_disease avg_glucose_level

A sample of 120 patients taken from the dataset was utilised to assess the model. It should be noticed that the target variable's values in the dataset are binary values, as illustrated in Figure 3. (0 and 1). In our instance, the model's output is expressed as a probability, with a cut-off value of 50%. The received findings were then assessed and contrasted with those anticipated. Tables 3-5 chart the development of the findings using the various models that were examined and discussed previously.

Model 3 utilised Model 2's features and design while implementing the PCA algorithm.

Table 2: final architecture of a neural network

Optimizer	Adam

Hidden layers	1 hidden layer with 9 neurons
Activate hidden layer function	Relu
Dropout grade	0.20 (in hidden layer and input layer)
Learning rate	0.001
Batch size	10
MaxNorm	3
Epochs	200
Validation Split	0.15
Output layer activation function	sigmoid

Table 3: Model 1's characteristics (correlation matrix) and architecture

Features providing best results	
age	
hypertension	
heart_disease	
ver_married avg_glucose_level	
Optimizer	Adam
Hidden layers	1 hidden layer with 9 neurons
Activate hidden layer function	Relu
Dropout grade	0.20 (in hidden layer)
Learning rate	0.001
Batch size	10
MaxNorm	3
Epochs	200
Validation Split	0.15
Output layer activation function	sigmoid

Table 5 shows that model 1 offers a 77.5% success rate. In order to evaluate multiple models in an empirical manner, we added and removed features from model 2 once it was seen that some characteristics added noise to the model. Up to 80% more success might be achieved using the traits listed in Table 4. For model 3, we applied the PCA method using the same structure and traits as in model 2, testing with various numbers of components, and getting the best results with 4 components, with 82% accuracy. It can be seen in generic terms.

Table 4: Characteristics of model 2 (trying different aspects) and its architecture

Features providing best results	
sex age	
hypertension	
heart_disease avg_glucose_level	
Optimizer	Adam
Hidden layers	1 hidden layer with 9 neurons
Activate hidden layer function	Relu
Dropout grade	0.20 (in hidden layer and input layer)
Learning rate	0.001

Batch size	10
MaxNorm	3
Epochs	200
Validation Split	0.15
Output layer activation function	sigmoid

Table 5: Assessment of the models employed

MODEL 1		
	Predicted yes	Predicted no
True yes	40	6
True no	21	53
Accuracy	77.50%	
MODEL 2		
	Predicted yes	Predicted no
True yes	37	10
True no	14	59
Accuracy	80.00%	
MODEL 3 (PCA)		
	Predicted yes	Predicted no
True yes	40	7
True no	15	58
Accuracy	82.00%	

3.2. Mobile Application

The open-source Flutter SDK and the Dart programming language were utilised to create the mobile application. This Google-developed programming language is used to construct desktop, online, back-end, and mobile apps. Dart is an object-oriented language with a C-style syntax that is defined by classes, however in other ways it is similar to Java, Python, and Java. In contrast, Google has also developed Flutter, an SDK that enables the development of cross-platform mobile applications. The primary benefits of Flutter are native compilation with great performance for both Android and iOS, extremely flexible construction of graphical user interfaces, and quick development.

As only minor coding modifications are required to produce versions for the two most popular mobile platforms right now—iOS and Android—it was chosen to use a mobile application as the user interface.

The user interface was created with non-technical healthcare staff in mind, and it is appealing, simple, and easy to use. The application's first iteration concentrated on the doctor's function, enabling them to access patient data, review laboratory analytical findings, and determine the likelihood that a patient would contract a certain ailment for which the system has a pre-trained model (cerebral stroke in this case).

Figure 8 displays a few of the application panels that demonstrate some of the functionalities that have been developed. The user login screen, the profile information assigned to the current user, the patient search screen, and the current patient information form, which includes the results of the most recent laboratory tests and an estimate of the likelihood that a particular patient will contract a disease, are shown from left to right. Also, the programme enables the definition of several colours based on the range of determined probabilities of contracting a disease.

3.3. Database System

The application's database architecture is an essential component of the system since it must enable the simple storing of various models to assist in the diagnosis of various ailments. Medical facilities, users, patients, and the relevant clinical data for each of the diseases that will subsequently be used by the system as input for the ANN must also be included in the database. Data from different laboratory tests, such as imaging, blood, and urine tests, etc., as well as demographic information like sex, age, location, height, and weight are all included in patient information. Figure 9 depicts the database's entity-relationship

model together with the system's primary tables and relationships.
Oracle was chosen as the Database Management System (DBMS) for this project primarily due to its popularity, ability to be compatible with many clinic and hospital systems, and level of protection it provides. As patient clinical data must be saved in this instance, safety must be given extra consideration.

Figure 8: Some of the mobile app's displays

3.4. Building REST API's

Python was once more utilised for API programming using the Flask framework. This framework enables rapid, easy development of web applications and services. Integration with neural network models is more intuitive as a result of the API's Python development. The https protocol is used for communication between the API and the mobile application. The API processes the https queries sent by the mobile application and delivers the outcome in JSON format.
A REST API is included in the established system and serves as a middleman between the mobile application and the database. The programme may be simply customised to function with many ANN-based models saved in the database thanks to this method, regardless of the input variables used in each specific model. Every single function that has been built adheres to the flow diagram in Figure 10.
The many methods contained in the created API are displayed in Table 6, along with a description of their operation and the input parameters:

4. Model assessment

The experiments carried out to confirm the system's proper operation are described in this section. In order to assess the reliability of the findings and the development of each patient's forecast of developing a stroke event based on the demographic data and laboratory tests completed, we ran multiple experiments with five patients of varied ages.
To do this, the five most pertinent characteristics acquired using PCA, employed by the model as outlined in Section 3.1 Neural Network Architecture, have been retrieved using analytical records created by patients over time. Table 7 displays the data utilised for each patient as well as the model's predictions. The results of three laboratory tests taken throughout time, together with Sex and Age, have all been taken into account for each of the five patients. The patient names are made up because they have been anonymised.

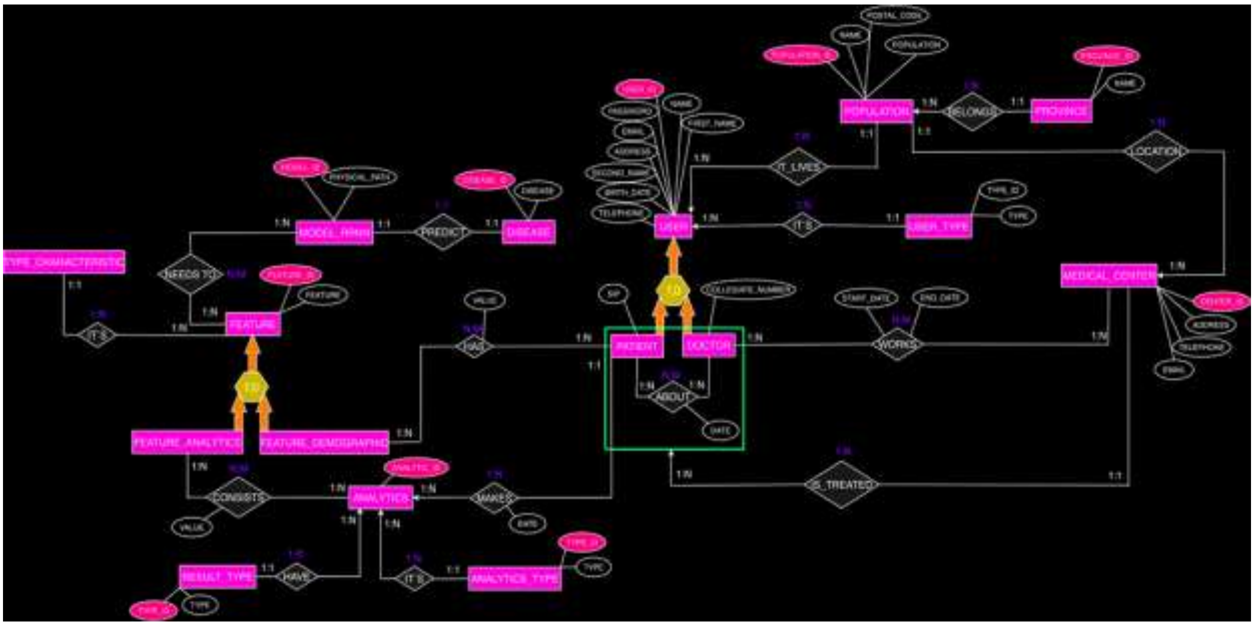

Figure 9: The database's entity-relationship design

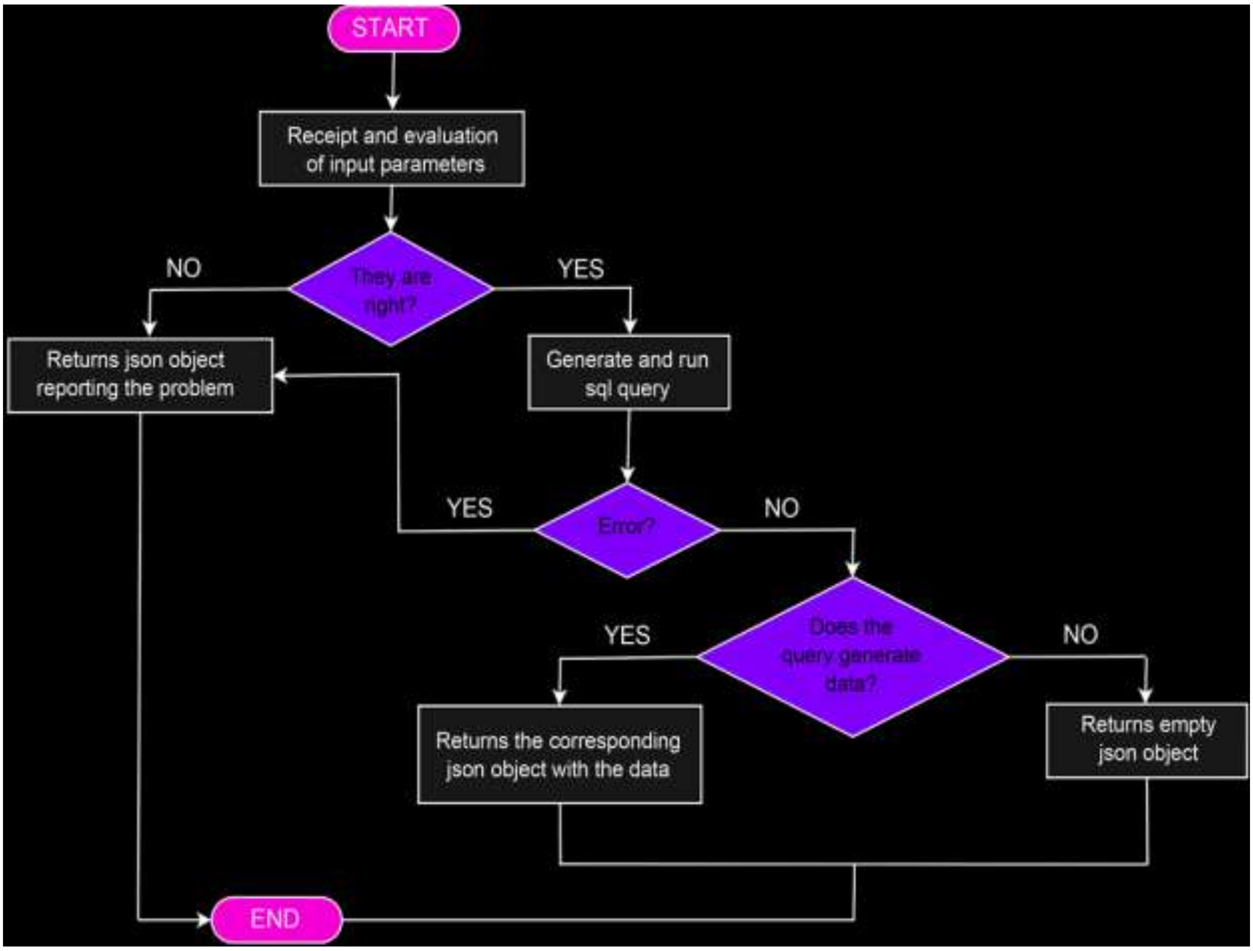

Figure 10: flowchart for API methods

The evolutionary graphs for each of the patients in Table 7 are displayed in Figure 11. One may see the outcomes of the model as well as the trend in each patient's likelihood of developing the condition over time.

The findings demonstrate that our Neural Network's estimation of the model is compatible with the evolution of the data supplied as input to the model, despite the fact that the goal of the current study was not to attain high accuracy in the estimation of the model. In any event, the created system is adaptable to other illnesses or even models, including those of the state of the art stated in Section 2: Relevant Work, as long as they are founded on utilising Artificial Neural Network models, as discussed in the preceding sections.

5. Conclusion and future scope

In this study, a novel AI-based approach that enables the storage of several previously trained ANN models to support illness detection has been suggested. This first functional prototype is made up of a multi-platform application with a mobile device-friendly user interface, a database for storing the models, a first ANN model with an appropriate architecture for cerebral stroke prediction, and a rest API that serves as a middleware between the user interface and the database and enables the system to be easily scaled to new diseases and models.

Although there is only one model in this initial version of the tool, the trials conducted demonstrate that it works as intended and inspire us to add more models and illnesses in subsequent iterations. The findings of the experiment demonstrate that our ANN Network's estimation is compatible with the evolution of the data that was supplied as input to the model.

Table 6: Methods of API

METHOD	**PARAMETERS**	**DESCRIPTION**
/file	Patient id	Returns the data (personal and medical) of the patient specified as a parameter.
METHOD	PARAMETERS	DESCRIPTION
/doctor	Doctor id	Returns the data of the physician specified as parameter.
METHOD	PARAMETERS	DESCRIPTION
/statistics	Patient id	Using the patient’s identifier included as a parameter, it retrieves the previously trained models from the database and returns a prediction of the probability of suffering a certain disease for each of them.
METHOD	PARAMETERS	DESCRIPTION
/analytical_values	Analytic id	Returns the values of a specific laboratory analysis based on its identifier
METHOD	PARAMETERS	DESCRIPTION
/analytics	Patient id	Given the id of a patient, this method returns the laboratory tests stored in the database ordered by most recent date.
METHOD	PARAMETERS	DESCRIPTION

/patients	Doctor Id. Filter [Optional]	If the filter parameter is not specified, the method returns all patients associated with the doctor whose identifier matches the one specified as a parameter. If the filter parameter is specified, a search is made for patients in the database
METHOD	PARAMETERS	DESCRIPTION
/login	Nickname, Password	This method is used to authenticate a user, using their username and password

First and foremost, new models for various diseases will be created and included as future work. In particular, we are developing a model for the early diagnosis of urinary tract infection to ascertain whether antibiotics should be prescribed before the results of the patient's culture are available, which might greatly speed up the patient's recovery. In order to make the process of adding a new model to the system as simple as feasible, a graphical user interface is also being designed for the development and training of new ANN models.

Table 7: Development of patient biological and demographic data, as well as the identification of disease

Héctor date Analytic	Sex	Age	INPUT DATA hypertension heart_disease	Avg_glucose_level (mg/dl)	MODEL OUTPUT Prediction (%)
01/2017	Male	53	No No	113.21	32.75
04/2018	Male	54	Yes No	120.78	63.10
07/2020	Male	56	Yes Yes	160.05	69.56
Raúl Date analytic	Sex	Age	INPUT DATA hypertension heart_disease	Avg_glucose_level (mg/dl)	MODEL OUTPUT Prediction (%)
02/2014	Male	66	No No	81.10	38.08
03/2019	Male	71	No Yes	102.36	69.59
02/2021	Male	73	Yes Yes	98.6	76.11
Carla Analytic Date	Sex	Age	INPUT DATA hypertension heart_disease	Avg_glucose_level (mg/dl)	MODEL OUTPUT Prediction (%)
03/2021	Female	55	Yes Yes	210.40	66.43
06/2021	Female	55	No Yes	190.47	63.26
09/2021	Female	55	No Yes	180.40	63.08
Toni Analytic Date	Sex	Age	INPUT DATA hypertension heart_disease	Avg_glucose_level (mg/dl)	MODEL OUTPUT Prediction (%)
02/2011	Male	78	No No	78.03	41.01
05/2017	Male	84	No Yes	80.12	41.91
06/2021	Male	88	No Yes	94.64	65.87
Ángela Analytic Date	Sex	Age	INPUT DATA hypertension heart_disease	Avg_glucose_level (mg/dl)	MODEL OUTPUT Prediction (%)

05/2019	Female	71	Yes No	195.25	60.62
06/2020	Female	72	Yes No	180.63	61.21
08/2021	Female	73	Yes No	161.21	62.10

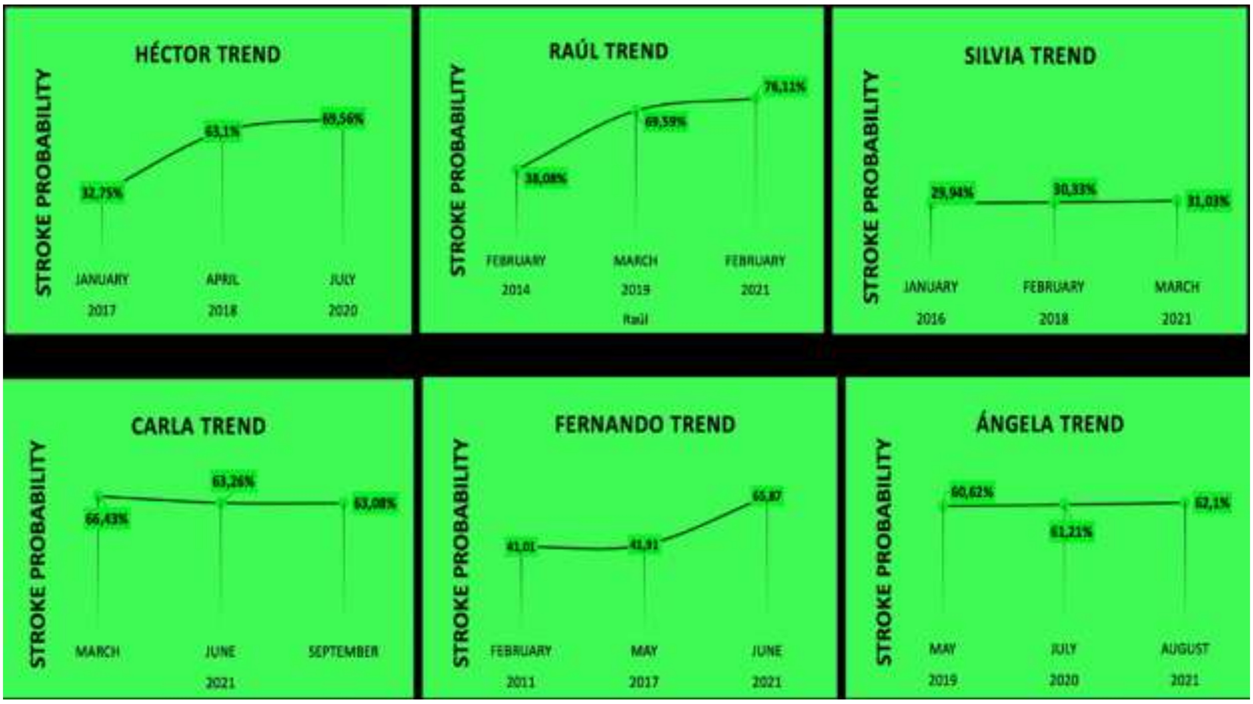

Figure 11: Patients' output from the model

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