wjert, 2024, Vol. 10 Issue 8, 83-92. *Original Article* ISSN 2454-695X

World Journal of Engineering Research and Technology

WJERT

www.wjert.org

SJIF Impact Factor: 7.029

SMART STROKE PREDICTION

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Article Received on 25/05/2024 **Article Revised on 15/06/2024** **Article Accepted on 05/07/2024**

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ABSTRACT

This IoT project aims to develop a comprehensive Brain Stroke Detection and Notification System utilizing an ARM microcontroller and machine learning techniques. The system collects vital health data, including ECG values from an ECG sensor, heartbeat data from a heartbeat sensor, temperature measurements using a temperature sensor, and blood pressure (BP) and SpO2 data from a MAX3050 sensor. These real-time data streams are displayed on an LCD for immediate monitoring and are wirelessly transmitted through Zigbee communication to a central hub.

KEYWORDS: An ARM microcontroller and machine learning techniques, ECG sensor, heartbeat data from a heartbeat sensor, temperature measurements using a temperature sensor, and blood pressure (BP) and SpO2 data from a MAX3050 sensor.

INTRODUCTION

The Significance of This Project Lies Not Only In Its Potential To Improve Stroke Prediction Accuracy But Also In The Broader Implications for Preventive Healthcare. If successful, the Developed Model Could Serve As A Valuable Tool For Clinicians In Identifying High-Risk Individuals and Implementing Preventive Measures Tailored To Individual Patient Profiles. Ultimately, this Research Seeks to Bridge The Gap Between Machine Learning Advancements And Practical Healthcare Applications, Fostering A New Era Of Personalized And Proactive Medical Interventions.[7]

The potential impact of this research extends beyond the realm of stroke prevention; it lays the groundwork for a broader paradigm shift towards proactive and personalized healthcare, where predictive models can empower clinicians with valuable insights for early intervention strategies tailored to individual patient profiles. Through this endeavor, we aspire to contribute to the advancement of healthcare practices, emphasizing the integration of cutting-edge technology to improve patient outcomes and ultimately save lives.

Olamilekan Shobayo.[2] This paper provides a comprehensive review and content analysis of current technology-enabled stroke rehabilitation strategies, exploring the evolving landscape of technological interventions for stroke survivors. It delves into diverse aspects, including virtual reality, exoskeletons, and artificial intelligence (AI), shedding light on the potential for enhanced rehabilitation and reintegration into daily life.

Chi Sang Choy; Shaun L. Cloherty; Elena Pirogoya[3] Focused on virtual reality-assisted motor imagery, this review explores its potential as an intervention for early post- stroke recovery. The paper investigates how virtual reality technologies can facilitate motor imagery, providing a nuanced understanding of their impact on motor rehabilitation in the acute stages of stroke.

Yang-An Li; Ze-Jian Chen; Chang He.[5] This paper explores the impact of exoskeleton-assisted sit-to-stand training on lower-limb function in subacute stroke survivors. It delves into the modifications of This paper explores the impact of exoskeleton-assisted sit-to-stand training on lower-limbfunction in subacute stroke survivors. It delves into the modifications of muscle synergies, shedding light on the biomechanical aspects of exoskeleton interventions for improving functional outcomes in this specific population.

Sejuti Rahman; Sujan Sarker; A. K. M. Nadimul Haque[6] This systematic review explores the landscape of artificial intelligence- driven stroke rehabilitation systems and assessments. It investigates how AI technologies contribute to personalized and adaptive rehabilitation interventions, offering insights into the evolving role of AI in stroke recovery.

Rui Zhang; Chushan Wang; Shenghong He; Chunli Zhao Summary[7] Focusing on adaptive brain-computer interfaces, this paper explores their role in enhancing motor recovery after stroke. It delves into the mechanisms by which brain-computer interfaces adapt to individual neurophysiological variations, providing insights into their potential as personalized tools for stroke rehabilitation.

Michael Glassen; Gregory Ames; Guang Yue.[8] This paper investigates the cortico-muscular connectivity during standing in the early post-stroke period using electroencephalography (EEG). It explores the neural mechanisms underlying post-stroke standing stability and provides insights into the interplay between cortical and muscular activity during this critical phase of recovery.

Rui Xu; Haichao Zhang; Xinyu Zhao.[9] Focusing on functional electrical stimulation (FES), this paper explores its impact on cortical activity and synchronization in stroke survivors. It investigates the use of contralaterally controlled FES to enhance symmetrical neural responses, offering insights into the potential neuro rehabilitative effects of this intervention.

K. Cowell; T. Y. Pang; J. S. Kwok.[10] This paper addresses the feasibility of miniaturizing computed tomography (CT) technology for mobile stroke units. It explores the challenges and opportunities associated with downsizing CT technology, aiming to facilitate efficient and timely stroke diagnosis in mobile healthcare settings Technical and logistical challenges in miniaturizing CT technology may pose obstacles, and the generalizability of findings to diverse healthcare infrastructures requires consideration.

Karen J. Nolan; Gregory R. Ames; Christina M. Dandola[11] Focused on exoskeleton gait training, this paper investigates the impact of intensity modulation on post-stroke gait rehabilitation. It explores how adjusting training intensity in exoskeleton-assisted gait rehabilitation can influence functional outcomes, offering insights into optimizing rehabilitation protocolsThe study's focus on intensity modulation may require further investigation into its long-term effects, and a broader sample size could enhance the generalizability of results.

Mengmeng Liu; Guizhi Xu; Hongli Yu[12]**:** Limited longitudinal data may hinder a comprehensive understanding of the sustained effects of tDCS, and the generalizability of findings to diverse stroke populations requires consideration This paper investigates the effects of transcranial direct current stimulation (tDCS) on electroencephalography (EEG) power and brain functional networks in stroke patients. It explores how tDCS modulates neural activity and connectivity, providing insights into the neurophysiological changes induced by this non-invasive brain stimulation technique.

II. METHODOLOGY

A. Data Collection

An organised and mathematical dataset was taken from the ECG. Considerations are made for the heart rate, Blood pressure, temperature, and oxy rate. The hospital Machine Learning data providers provided the dataset used in this work. A csv file is then created and used to hold the data.

B. pre-processing

Due to missing values and inconsistent data, the dataset cannot be handled in the classification process. More variables were deleted since they were the same for each subject. Invariant qualities are evaluated using the variance or standard deviation value. Average values are used to fill in the remaining missing data.

C. Feature Extraction

There are two methods for selecting features: Random Forest and Principal Component Analysis (PCA). The preprocessed data includes a lot of characteristics, and the categorization approach we chose requires a lot of effort. Feature selection is essential to save time and acquire the most significant characteristics that are most closely related to the output class. In the taken dataset the data might be repeated or they might be repetation of the disease so in order to remove that here the random forest algorithm is used to classify between the dataset and help to reduced the given data.

D. Model Architecture

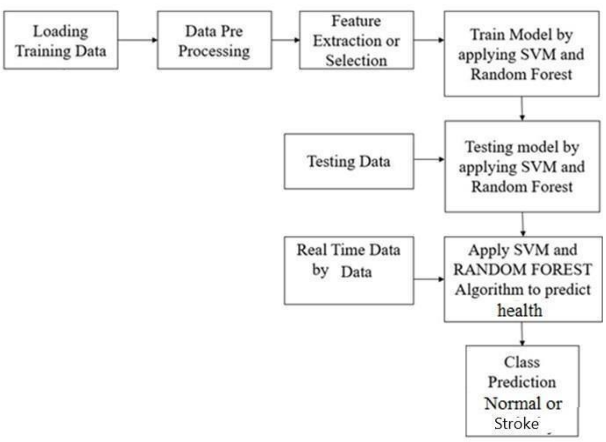


Fig. 1: Customized model architechture.

a) Importing Libraries: Numpy‟ is a Python module for scientific computing. This library will be utilised throughout the project and is imported as 'np',, pandas‟ is used to manipulate and analyse data. pandas is a BSD-licensed open source library with basic data structures and data analysis skills as pd, the pandas package is imported,, seaborn‟ is a Python data visualisation package for appealing and useful statistical visuals based on matplotlib.

Data Pre-processing For the purpose of removing pertinent information from the input pictures, the CNN uses many convolutional layers. The layers provide feature maps that capture key object features using convolution with various kernels. For thorough feature extraction, our design uses a mix of filters in these levels. In order to efficiently capture different characteristics, the second convolutional layer includes a higher number of filters of different sizes than the first layerChecking for NaN is critical during data pre- processing. We were only able to find a few NaNs in this try. Changing the value of NaN It's critical to get rid of the NaN values. This may be accomplished by: removing the whole column having a large number of NaN values Method of forward fillna Method of backward fillna Using the mean technique.

b) Data Analysis: Data analysis is the process of dissecting, sanitising, modifying, and modelling data with the aim of revealing relevant information, guiding deductions, and assisting in decision making. Data analysis has many different components and steps, including a wide variety of methods with different names that are applied in a number of business, scientific, and social science fields. Because it helps businesses to operate more efficiently and make more scientific judgments, data analysis is essential in today's business environment.

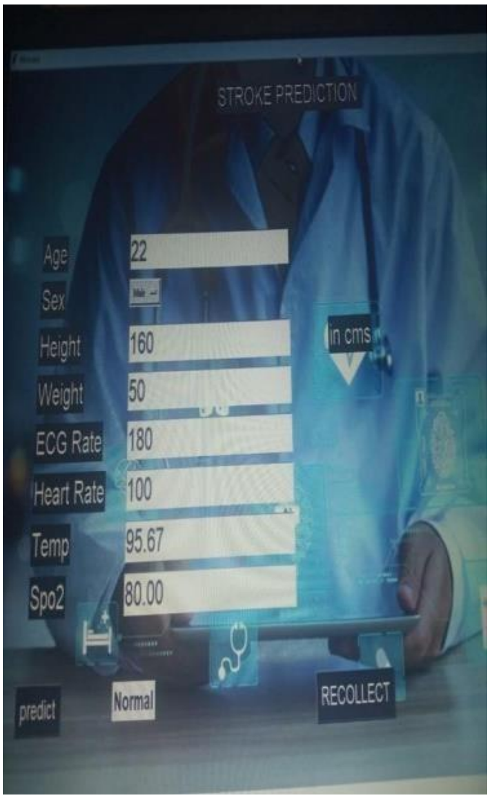
c) Feature Extraction: Feature extraction is the process of converting raw data into numerical traits that may be used while keeping the specifics of the original data set. Compared to just applying machine learning to raw data, it produces superior outcomes. As a consequence, when training a dataset, it is possible to quantify how much each feature lowers impurity. The greater an attribute's ability to eliminate impurity, the more significant it is. In random forests, the impurity decrease from each feature may be averaged across datasets to determine the variable's final significance.

III. RESULTS AND DISCUSSIONS

By Leveraging Technology And Data Analytics, A Smart Stroke Prediction System Aims To Provide Early Detection And Personalized Risk Assessment, Empowering Individuals To Take Proactive Steps To Mitigate Their Stroke Risk And Improve Their Overall Health Outcomes.

TABLE I.

AGE	SEX	HEIGHT	WEIGHT	ECG RATE	HEART RATE	TEMP	SPO2	RESULT
22	MALE	160	50	180	100	95.67	80.00	NORMAL
22	MALE	160	48	110	80	97.67	60.00	NORMAL
21	FEMALE	150	53	100	90	95.67	70.00	NORMAL
21	FEMALE	155	42	110	100	96.67	80.00	NORMAL



Smart stroke prediction systems typically utilize artificial intelligence algorithms, particularly machine learning techniques, to analyze various risk factors and predict the likelihood of an individual experiencing a stroke. These systems often incorporate data such as medical history, lifestyle factors, demographics, and sometimes genetic information to make accurate predictions.

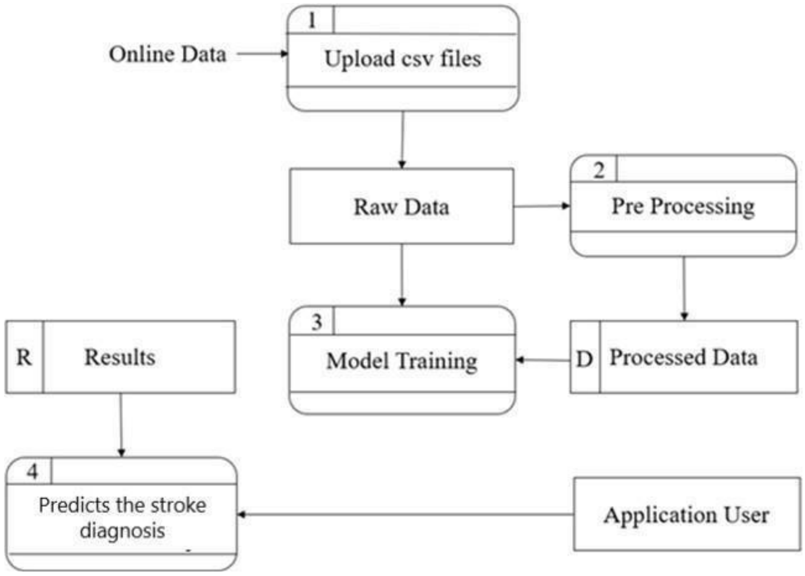
Table II: Model Performance In Our Expermiment Using Dropout.

Name of Test: -	Stroke Detection with Input values
Item being tested: -	Input from user and cloud
Sample Input: -	Sensor and Manual Input values
Expected output: -	Should Detect stroke
Actual output: -	Same as Expected
Remarks: -	Pass.

TABLE III.

Name of Test: -	System testing
Item being tested: -	Synchronization
Sample Input: -	Give Inputs to all Sensors
Expected output: -	Device Should Perform all actions according to input
Actual output: -	All Functions Worked Properly
Remarks: -	Pass

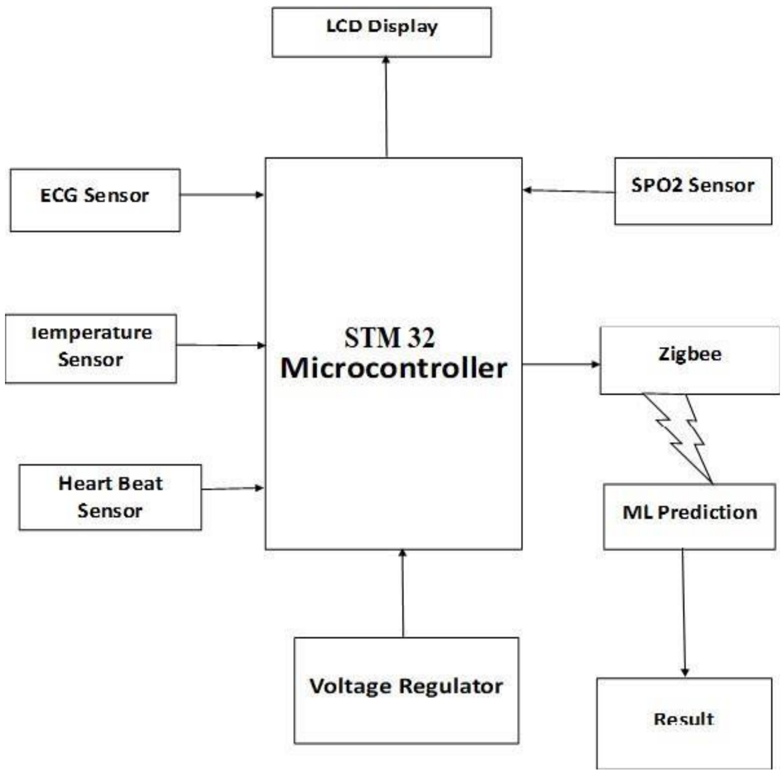
System testing enables us to test, verify, and validate both the business requirements as well as the application architecture.



A data flow diagram (DFD)

it indicates the different types of data that data input into the system, data output from the system, data flow through the system, and data storage.

Block Diagram



The system gathers relevant data from various sources. This can include personal health records, medical history, lifestyle factors (such as smoking or exercise habits), physiological data (like blood pressure and cholesterol levels), and genetic information. Wearable devices like smartwatches or fitness trackers may also provide real-time health data. Once the data is collected, it undergoes processing to clean and organize it. This step involves handling missing or inconsistent data and preparing it for analysis. Advanced analytics techniques, including machine learning algorithms, are then applied to this data to identify patterns and relationships that may be predictive of stroke risk.

IV. CONCLUSION

In conclusion, this project has undertaken a comprehensive exploration into stroke prediction using machine learning, with a specific emphasis on the Random Forest algorithm. By integrating diverse patient attributes and leveraging a robust predictive model, the project aims to make significant strides in early stroke detection. The user- friendly interface ensures practical applicability in clinical settings, empowering healthcare professionals with a valuable tool for timely intervention and personalized care.

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