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STROKE ASSISTANCE FOR PATIENTS

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Abstract: Stroke is a prominent global health issue, ranking as the leading cause of disability and the second leading cause of death. Stroke is a major cause of disability and death worldwide, with significant social and economic implications. It is a debilitating and potentially fatal disorder caused by a reduction or cessation of blood circulation to the brain, which damages or kills brain cells. The rising number of stroke survivors needs enhanced neurorehabilitation procedures. In response to the growing number of stroke survivors and the critical need for effective therapies, a Clinical Decision Support System (CDSS) mobile app is being created to transform stroke care. The software combines innovative technology with medical experience to expedite decision-making workflows for healthcare workers, addressing the critical requirement for quick and accurate interventions in stroke management. Focusing on stroke severity assessment, evidence-based protocol implementation, and personalized patient care, the app provides real-time access to critical information and diagnostic support. Additionally, it encompasses features such as risk assessment, medication management, telestroke consultations, and personalized rehabilitation planning. The CDSS app not only serves as a reliable companion for clinicians but also fosters interdisciplinary collaboration, facilitates telehealth consultations, and encourages continuous learning through data analytics. By offering real-time access to critical information and diagnostic support, along with features like risk assessment, medication management, telestroke consultations, and personalized rehabilitation planning, the CDSS app aims to bridge gaps in stroke care delivery, enhance patient outcomes, and advance healthcare practices.

Keywords: Stroke Management, Clinical Decision Support System, Stroke severity assessment, personalized healthcare, medication management, advanced healthcare practices

I. INTRODUCTION

Brain stroke, also known as a cerebrovascular accident (CVA), is a severe and potentially fatal disorder caused by a decreased or halted blood supply to the brain, which damages or kills brain cells. Because of its high frequency, high fatality rate, and long-term disability among survivors, it is a serious global health issue.[2]

Hemorrhagic and ischemic brain hemorrhages are the two primary forms of brain hemorrhage. Ischemic strokes happen when a blood clot obstructs or narrows a blood artery that supplies blood to the brain. Hemorrhagic strokes occur when a weak blood vessel bursts, allowing blood to enter the brain. Hypertension, smoking, diabetes, high cholesterol, obesity, sedentary lifestyle, poor diet, alcohol usage, obesity, genetic predisposition, stress, and depression are common risk factors for stroke. High blood pressure is one of the most significant clinical risk factors for stroke. Stroke survivors may face physical impairment, difficulty communicating, loss of employment and money, and a breakdown in social networks.[1][2]

Stroke is the second leading cause of death and disability in the globe. According to the Global Stroke Fact Sheet issued in 2022, 1 in every 4 people are anticipated to experience a stroke in their lifetime, and the lifetime likelihood of having one has risen by 50% during the previous 17 years.Between 1990 and 2019, stroke incidence rose by 70%, death by 43%, prevalence by 10%, and Disability Adjusted Life Years (DALY) by 143%. Lower- and lower-middle-income countries had the highest proportion of stroke-related mortality

(86% of DALYs and 89% of deaths). For families with fewer resources, this disproportionate burden faced by lower- and lower-middle-income countries has presented an unprecedented challenge.[1][2]

Brain Stroke can affect individuals of all ages, but the risk increases with age. The majority of stroke cases occur in individuals over the age of 65, although there is a concerning trend of rising stroke incidence among younger adults, attributed to lifestyle factors such as poor diet, physical inactivity, and rising rates of obesity. Additionally, stroke affects both genders, although men have a slightly higher risk compared to women.However, women tend to have poorer outcomes and higher mortality rates after stroke due to various factors such as hormonal fluctuations and differences in healthcare-seeking behavior.[2][3]

Despite advancements in medical technology and treatment modalities, stroke remains a significant challenge due to delays in recognition, diagnosis, and treatment. A Computerized Clinical Decision Support System (CDSS) utilizing the latest technologies such as Artificial Intelligence (AI) and Machine Learning holds promise in overcoming these challenges. A CDSS can help healthcare providers make timely and accurate decisions, resulting in improved stroke outcomes through the integration of patient data, clinical imaging, or evidence-based guidance. In addition, access to stroke care in underserved areas can be improved by mobile health applications and telemedicine platforms, facilitating early intervention and rehabilitation services.[1][2][3]

II.Literature Review

Many important studies and model building projects have been undertaken to detect strokes or determine the likelihood of a stroke occurring using a variety of machine learning approaches using patient datasets and electronic health information. As a result, we conducted important research that provided us with clarity and direction when carrying out our duties. This motivated us to interact with doctors and seek their guidance, consult published articles, and take into account numerous other viewpoints that significantly advanced our understanding and helped streamline our work. As a result, we developed a thorough study on the referred papers that is briefly described below, based on the objective, observation, evaluation metrics, and system development.

[4] conducted a systematic review on stroke management and CDSS effectiveness, focusing on diagnostic approaches. CDSS systems, depicted through diagrams, enhance clinical decision-making with machine learning techniques like SVM, ANN, and RF. Application scope covers follow-up, prevention, diagnosis, treatment, and guideline management. Performance evaluation considers functional and non-functional requirements, including accuracy, sensitivity, specificity, completeness, precision, and F1-score.

[5] stresses enhanced patient management via systematic mining of medical records for stroke prediction. Key factors like age, heart disease, hypertension, and glucose levels in EHR are highlighted. Correlation analysis and PCA are used to identify relevant features. Models such as Neural Networks, Random Forest, and Decision Tree were evaluated. Random Forest demonstrated the highest accuracy, depicted by a bell curve plot.

[6] delves into the use of Open Access Data for studying brain stroke diagnosis and prognosis, highlighting a gap in research focus compared to heart stroke. SMOTE pre-processing balances datasets and manages outliers. Validation sets are advocated to prevent overfitting. Various algorithms like Random Forest, Decision Tree, and Logistic Regression were evaluated with explanation diagrams and confusion matrices. Histograms visualize data based on gender, age, BMI, glucose levels, and hypertension. Color scales are utilized to indicate parameters' contributions to stroke occurrence. Random Forest exhibits the highest accuracy, although other studies note limitations, citing a 73% accuracy based on dataset specifics.

[7] focuses on parameter determination for stroke prediction using EHR data. Various patient attributes including age, gender, hypertension, heart disease, marital status, occupation, residence type, glucose level, BMI, and smoking status were considered. Principal Component Analysis was employed, with each attribute's importance depicted diagrammatically by arrow lengths. Neural Network emerged as the best-performing model with 75.0% accuracy.

In studies like [8] and [9], a dataset of 512,726 participants was analyzed, focusing on lifestyle factors and physical features. Findings revealed that stroke occurrence correlated with age, heart disease, diabetes, and hypertension, with higher prevalence among older individuals. Men exhibited a higher stroke rate (9.5%) than women (7.9%). Variations in stroke incidence were observed across different geographical regions studied. The future scope suggests employing AI for automating tasks like image analysis and developing new tools for diagnosis and treatment, allowing clinicians to prioritize patient care.

Review papers [10] and [11] explore the role of CDSS in stroke prevention within primary care. They discuss various interventions focusing on risk assessment, management, and patient education. CDSS is praised for its potential to enhance clinical decision-making through evidence-based guidance. Effectiveness of components like alert systems and risk calculators in reducing stroke incidence is highlighted. Challenges in CDSS implementation in primary care, such as integration issues and provider acceptance, are addressed. Overall, the papers underscore CDSS's promising impact on optimizing stroke prevention and improving patient outcomes in primary care settings.

Hence, the reviewed studies demonstrate the potential of state-of-the-art technologies in stroke detection and analysis using datasets they considered for prediction and analysis and also based on the survey papers that they took into consideration.

III. PROBLEM DEFINITION

The focus of our work is to address the challenges in stroke care by developing a user-friendly Clinical Decision Support System (CDSS) mobile app "Neuro Native". Focused on streamlining decision-making for healthcare professionals, the app integrates several essential parameters (such as gender, age ,smoking status and hypertension) that help in offering real-time support, risk assessment, and personalized recommendations to enhance the efficiency and effectiveness of stroke management..

IV. METHODOLOGY

4.1 Conceptual Study

Based on the study of the literary papers ,taking into account the various interactions with experts and the future scope of studies and challenges mentioned, we aim to develop a mobile app named "Neuro Native" for the efficient use of both doctors and patients to provide personalized care and treatment of the patient along with prediction and regular follow-ups. Fig 1. shows the conceptual diagram of the app intended to be implemented with basic functionalities explained as follows.

Our App will include features like:
The Electronic Health Records (EHRs) section stores the records of all patients and the database stores the records of patients currently being treated.

The patient is presented with a dashboard and can answer a questionnaire that will consist of basic questions to predict stroke using score based on demographics, parameters used to evaluate the questionnaire, and with the help of the doctor's (expert) advice. The CDSS will consider previous cases, required parameters, and EHR data to detect stroke.

If positive, the patient will be given the option to book an appointment and if negative, he or she will be suggested diet plans, therapy, and other preventive measures.

On booking the appointment, it will be visible to the doctor on his/her dashboard. The doctor can view the patient profile on the EHR cloud. After the appointment, the patient is sent timely medicine reminders and also can book a follow-up appointment.

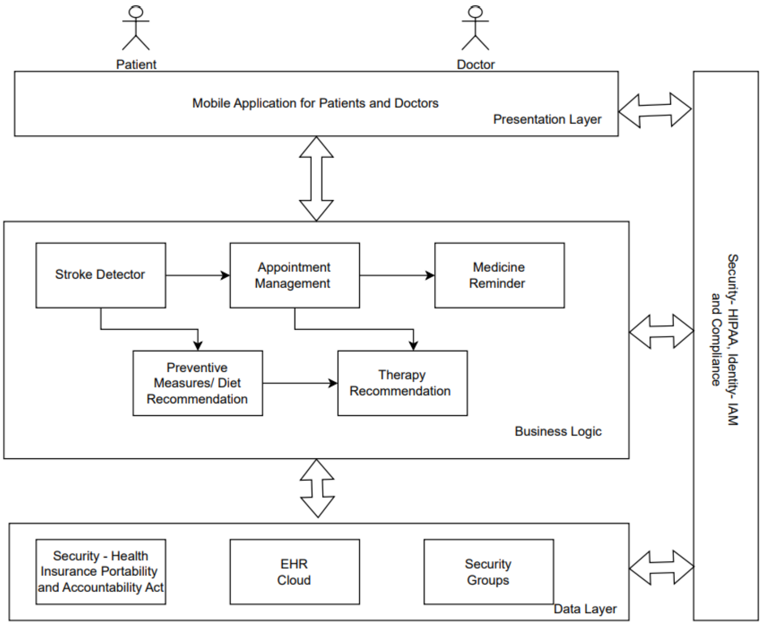

fig1. Concept Diagram

4.2 Patient Workflow

Given Fig.2 is the patient workflow diagram that helps in a greater understanding of how in a user-friendly way a patient can easily use the app. It illustrates key stages in stroke prevention and management. It encompasses patient registration, data collection, risk assessment, and generation of alerts for healthcare providers. Through decision support and care coordination, the CDSS aids in timely interventions and patient education, enhancing stroke prevention efforts in primary care settings. The various functionalities ,services offered for the patients and the process of using the app is as follows.

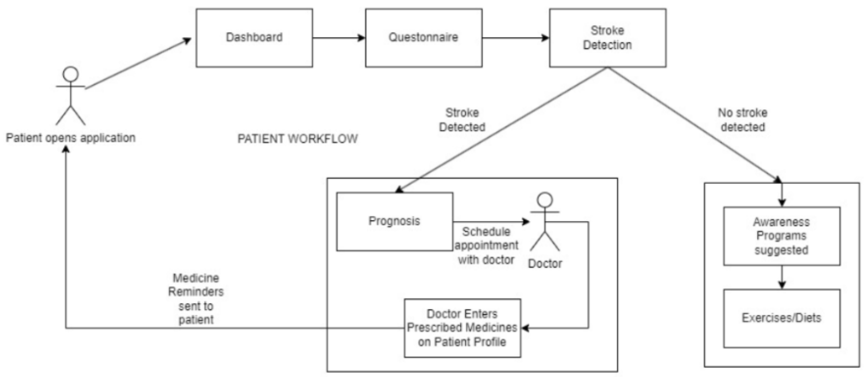

fig2. Patient Workflow Diagram

1. Unique Patient ID generated on registration
2. Ask basic questions like height, weight, BMI, Marital status, and Smoking habits.
3. Patient answers Questionnaire
4. Answers are stored on the EHR cloud
5. The result of the diagnosis is displayed to the patient
6. Depending on the result, the patient is either recommended diet plans or preventive measures or given a list of doctors for appointments.
7. After the appointment is booked, it is sent to the respective doctor
8. The patient is sent reminders of his/her appointment
9. The patient can also book a follow-up appointment with the same doctor

Some basic facilities on the doctor counterpart includes:

1. The doctor can log in using a unique Doctor ID
2. A list of upcoming appointments is displayed on the dashboard
3. The doctor can view the profile of any patient and after the appointment, enter the prescribed medicines so that the patient is sent timely reminders for the same.

V. IMPLEMENTATION

5.1 Technology Stack

The implementation of our stroke prediction system relies on a carefully selected technology stack to ensure efficiency, scalability, and user-friendliness. We choose React Native for mobile application development and Firebase for backend services.

React Native offers a powerful framework for building cross-platform mobile applications using JavaScript and React. Leveraging React Native enables us to develop a single codebase for both iOS and Android platforms, streamlining the development process while delivering a native-like user experience.

Firebase provides a comprehensive suite of backend services, including authentication, real-time database, cloud storage, and hosting. By utilizing Firebase, we can seamlessly integrate user authentication, data storage, and server-side functionalities into our application, simplifying development and deployment.

5.2 Model Training

In our stroke prediction system, we employ the Random Forest algorithm for training the predictive model. Random Forest is an ensemble learning method known for its effectiveness in classification tasks, particularly when dealing with complex and heterogeneous data.

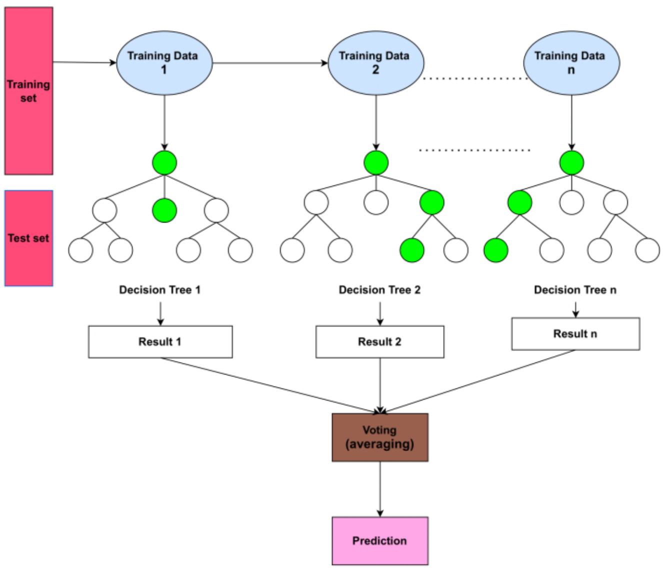

fig3. Random Forest Algorithm

Figure 3 depicts how the Random Forest Algorithm operates. During the training phase, the Random Forest Algorithm generates a large number of decision trees before selecting the class that appears the most frequently among these trees to be the output. This ensemble strategy effectively combats overfitting and improves the model's generalizability, making it suitable for our predictive modeling purposes.

5.3 Data Preprocessing

Before training the Random Forest model, extensive data preprocessing is performed to guarantee that the input data is of good quality and fit. This step involves handling missing values, encoding category variables, scaling numerical features, and dividing the dataset into training and testing sets.

In order to extract pertinent features and improve the model's prediction capacity, we also perform feature engineering. By capturing significant patterns and correlations in the data, feature engineering approaches like feature creation, modification, and selection help us make predictions that are more accurate.

5.4 Model Training and Evaluation

We implement the Random Forest algorithm using the scikit-learn library in Python. The training process involves feeding the preprocessed dataset into the Random Forest classifier and tuning hyperparameters to optimize model performance.

We employ various assessment metrics, such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC), to evaluate the trained model. These measures help assess the model's effectiveness in predicting stroke risk and provide insightful information about its predictive power.

5.5 Integration with React Native and Firebase

Once the model is trained and evaluated, we integrate it into our React Native application using Firebase as the backend infrastructure. We implement user authentication and data storage functionalities using Firebase Authentication and Realtime Database, respectively, to securely manage user data and predictions.

The stroke prediction feature is seamlessly integrated into the application's user interface, allowing users to input relevant health information and receive personalized risk assessments in real-time. The integration with Firebase ensures reliable data transmission and storage, enabling a smooth user experience.

5.6 Deployment and Testing

Finally, we deploy the stroke prediction system to respective app stores for public access and conduct rigorous testing to ensure its reliability, performance, and user satisfaction.

VI. EVALUATION MEASURES

Thorough evaluation of machine learning models' or algorithms' performance is crucial for creating reliable and efficient solutions. Evaluation metrics offer important insights into the advantages and disadvantages of these models by acting as quantitative gauges for their effectiveness, precision, and dependability. This section delves into the thorough analysis that will be beneficial for our app in gaining access to the performance through a variety of metrics.

Because it directly affects how model performance is interpreted and how decisions are made thereafter, choosing the right evaluation metrics is crucial. We seek to guarantee a comprehensive comprehension of our model's behavior in various circumstances and datasets by utilizing a well-defined collection of metrics, which will enable well-informed decisions and optimizations. These measures cover a wide range of model performance parameters, such as accuracy, F1-score,precision, recall, (AUC-ROC) - area under the receiver operating characteristic curve, and more. Every statistic provides distinct insights into various aspects of the behavior of the model, allowing for a thorough assessment from several angles.

6.1 Confusion Matrix and Evaluation Measures

The confusion matrix (Fig.4) is a crucial instrument for evaluating the effectiveness of classification models, offering a detailed breakdown of predicted and actual class labels. Categorizing model predictions into four key groups—true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN)—the confusion matrix provides valuable insights into the accuracy of predictions and the model's misclassifications.

Essentially, the confusion matrix is a square matrix where every row signifies instances predicted for a specific class, and every column denotes instances belonging to an actual class. The diagonal elements (from top-left to bottom-right) indicate accurately classified instances, whereas the non-diagonal elements signify misclassifications.

Evaluation Measures: In conjunction with the confusion matrix, various evaluation metrics provide quantitative measures of a classification model's performance. Here, we introduce and define several key evaluation metrics commonly used in the assessment of classification algorithms:

Accuracy (ACC): The ratio of correctly predicted occurrences to all instances in the dataset is known as accuracy. It is calculated as follows and provides a general indication of the model's performance in all categories:

ACC = TP + TN/{TP + TN + FP + FN}

Precision (PR): Precision measures the percentage of actual positive forecasts among all positive predictions. It is computed as follows and focuses on the accuracy of positive predictions:

PR = TP/{TP + FP}

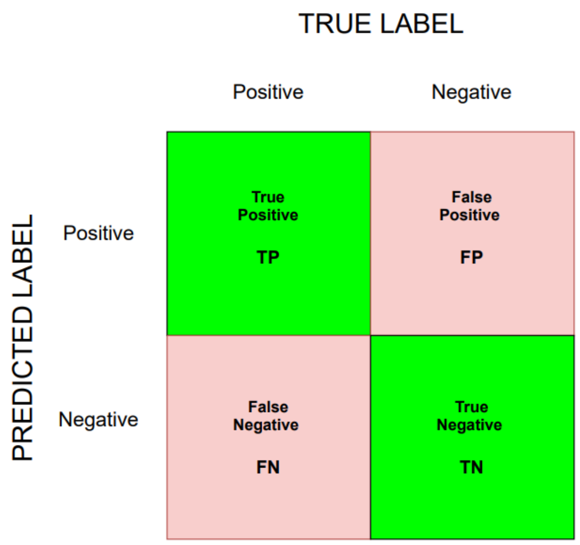

fig4. Confusion Matrix

Recall (RC): Recall quantifies the percentage of genuine positive cases that the model properly detected; it is also known as sensitivity or true positive rate. It assesses how effectively the model accounts for every instance of positivity and is based on:

RC = TP/{TP + FN}

F1-Score (F1): The F1-score, which is the harmonic mean of precision and recall, is a balanced indicator of a model's performance. It is computed as follows, taking into consideration both false positives and false negatives:

F1 = 2 * PR * RC/{PR + RC}

Specificity: Another name for specificity, is the percentage of genuine negative cases that the model properly detected. It is computed as follows and evaluates the model's accuracy in classifying negative instances:

SP = TN/{TN + FP}

6.2 Visualization : Box Plot Analysis

Box plots offer a graphical representation of the distribution of data, highlighting key statistical measures such as the median, quartiles, and outliers. By examining the distribution of age within each category of smoking status and gender, we aim to gain insights into how these factors interact and influence the likelihood of stroke occurrence.

For this analysis, we categorized individuals based on their smoking status (formerly smoked, never smoked, current smoker, unknown) , gender (male, female and other) and age. The dataset comprises 5000 entries having various set of parameters like gender,age,hypertension, bmi and many more. In total, 10 such parameters have been taken into consideration for the prediction of stroke, ensuring a robust representation of diverse demographic groups. Each box plot represents the distribution of ages within these categories, allowing us to visualize any differences or trends across different subgroups. Fig 5 below depicts the box plot representation of the dataset we are using based on the parameters such as age, smoking status and gender.

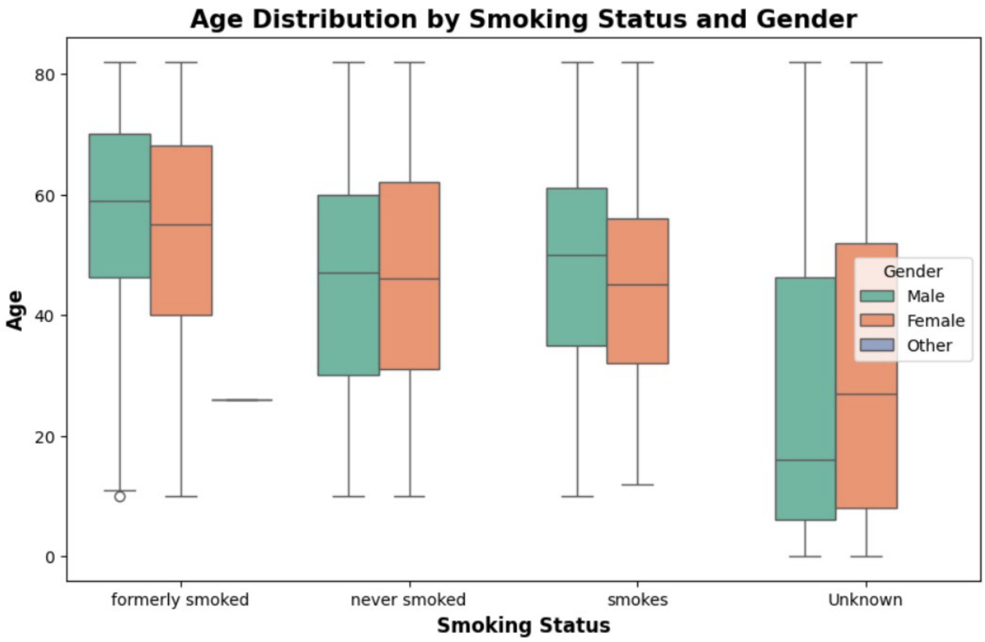

fig5. box plot representation

A wider spread or higher median within a particular category may indicate a potential association with increased stroke risk. Additionally, the presence of outliers can signify significant deviations from the general trend, warranting further investigation into potential risk factors. Thus, Box plots provide a concise summary of the distribution of a continuous variable across different categories, making them ideal for identifying patterns and variations within the data. It provides additional insights into the underlying factors influencing model performance and stroke prediction.

VII. CONCLUSION

The envisioned Clinical Decision Support System (CDSS) mobile app holds great promise for revolutionizing stroke care. The synthesis of advanced technology with clinical expertise is poised to reshape decision-making in the field. As we embark on this transformative journey, the potential impact on stroke management and patient outcomes underscores the significance of our yet-to-be-realized endeavor. The path ahead is one of innovation, collaboration, and a steadfast commitment to leveraging digital tools for the betterment of stroke care.

VIII. FUTURE SCOPE

Incorporating wearable devices or sensors that continuously monitor neurological parameters and feed data into the CDSS could facilitate early detection of stroke symptoms and prompt intervention, thus improving patient outcomes and reducing long-term disability.

REFERENCES

[1] World Health Organization, "World Health Organization (WHO) Definition of Stroke," Public Health, Aug. 17, 2020. https://www.publichealth.com.ng/world-health-organization-whodefinition-of-stroke/

[2] Brown, R. Stroke - Symptoms and Causes. Mayo Clinic (2023).. https://www.mayoclinic.org/diseasesconditions/stroke/symptoms-causes/syc-20350113

[3] National Institute of Neurological Disorders and Stroke, "Stroke," www.ninds.nih.gov, Mar. 08, 2023. https://www.ninds.nih.gov/healthinformation/disorders/stroke

[4] L. Souza-Pereira, N. Pombo, S. Ouhbi, and V. Felizardo, "Clinical decision support systems for chronic diseases: A Systematic literature review," Computer Methods and Programs in Biomedicine, vol. 195, p. 105565, Oct. 2020, doi: 10.1016/j.cmpb.2020.105565.

[5] S. Dev, H. Wang, C. S. Nwosu, N. Jain, B. Veeravalli, and D. John, "A predictive analytics approach for stroke prediction using machine learning and neural networks," Healthcare Analytics, vol. 2, p. 100032, Nov. 2022, doi: 10.1016/j.health.2022.100032.

[6] T. Tazin, N. Alam, N. N. Dola, M. S. Bari, S. Bourouis, and M. M. Khan, "Stroke disease detection and prediction using robust learning approaches," Journal of Healthcare Engineering, vol. 2021, pp. 1–12, Nov. 2021, doi: 10.1155/2021/7633381.

[7] C. S. Nwosu, S. Dev, P. Bhardwaj, B. Veeravalli, and D. John, "Predicting Stroke from Electronic Health Records," Jul. 2019, doi: 10.1109/embc.2019.8857234.

[8] A. Bivard and M. Parsons, "Artificial intelligence for decision support in acute stroke current roles and potential," Nature Reviews Neurology, vol. 16, no. 10, pp. 575–585, Aug. 2020, doi: 10.1038/s41582-0200- 390-y.

[9] E. M. Alanazi, A. Abdou, and J. Luo, "Predicting risk of stroke from lab tests using machine learning algorithms:
Development and evaluation of prediction models," JMIR Formative Research, vol. 5, no. 12, p. e23440, Dec. 2021, doi: 10.2196/23440.

[10] S. F. Alasiri, A. Douiri, S. Altukistani, T. Porat, and O. Mousa, "The Role of Clinical Decision Support Systems in Preventing Stroke in Primary Care: A Systematic Review," *Perspect Health Inf Manag.*, vol. 20, no. 2, p. 1d, Apr. 2023.

[11] M. Chun et al., "Stroke risk prediction using machine learning: a prospective cohort study of 0.5 million Chinese adults," Journal of the American Medical Informatics Association, vol. 28, no. 8, pp. 1719–1727, May 2021, doi: 10.1093/jamia/ocab068.

[12] M. Saxena, M. Choudhary, M. Deep, S. Bhamra, and M. Maru, "Issue 4 www.jetir.org (ISSN-2349-5162)," JETIR2204518 Journal of Emerging Technologies and Innovative Research, vol. 9, 2022.

[13] E. Akay, A. Hilbert, B. Carlisle, V. I. Madai, M. A. Mutke, and D. Frey, "Artificial Intelligence for Clinical Decision Support in Acute Ischemic Stroke: A Systematic Review," vol. 54, no. 6, pp. 1505–1516, Jun. 2023, doi: https://doi.org/10.1161/strokeaha.122.041442.

[14] E. Dritsas and M. Trigka, "Stroke Risk Prediction with Machine Learning Techniques," Sensors, vol. 22, no. 13, p. 4670, Jun. 2022, doi: https://doi.org/10.3390/s22134670.

[15] H. Abdu and G. Seyoum, "Sex Differences in Stroke Risk Factors, Clinical Profiles, and In-Hospital Outcomes Among Stroke Patients Admitted to the Medical Ward of Dessie Comprehensive Specialized Hospital, Northeast Ethiopia," Degenerative Neurological and Neuromuscular Disease, vol. Volume 12, pp. 133–144, Oct. 2022, doi: https://doi.org/10.2147/dnnd.s383564.

[16] "Automated Stroke Prediction Using Machine Learning: An Explainable and Exploratory Study With a Web Application for Early Intervention — IEEE Journals & Magazine — IEEE Xplore," ieeexplore.ieee.org. https://ieeexplore.ieee.org/document/10130159

[17] L. Shahmoradi, R. Safdari, H. Ahmadi, and M. Zahmatkeshan, "Clinical decision support systems-based interventions to improve medication outcomes: A systematic literature review on features and effects," Medical Journal of The Islamic Republic of Iran, vol. 35, no. 27, Apr. 2021, doi: https://doi.org/10.47176/mjiri.35.27.

[18] T.-M. Chang, H.-Y. Kao, J.-H. Wu, and Y.-F. Su, "Improving physicians' performance with a stroke CDSS: A cognitive fit design approach," Computers in Human Behavior, vol. 54, pp. 577–586, Jan. 2016, doi: https://doi.org/10.1016/j.chb.2015.07.054.