Automated Stroke Prediction Using Machine Learning: An Explainable And Exploratory Study With a Web Application For Early Intervention

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Abstract:

Stroke is a dangerous medical disorder that occurs when blood flow to the brain is disrupted, resulting in neurological impairment. It is a big worldwide threat with serious health and economic implications. To solve this, researchers are developing automated stroke prediction algorithms, which would allow for early intervention and perhaps save lives. The number of people at risk for stroke is growing as the population ages, making precise and effective prediction systems increasingly critical. The goal of this study was study aimed to achieve three objectives: (i) to create a trustworthy machine learning model to predict stroke disease, (ii) to address the severe class imbalance issue that results from the stroke patients' class being substantially smaller than the healthy class, and (iii) by using Mutual Information Score, Chi-Square Score, and ANOVA test, find the import feature(iv) to interpret the model output to gain a better comprehension of the decision-making process (v) balancing the dataset from the ratio of 19: 1 for No Stroke: Stroke to equal ratio using SMOTE Analysis (vi) Propose an End-to-End smart healthcare system through an android application. In a comparison examination with six well-known classifiers, the effectiveness of the proposed ML technique was explored in terms of metrics relating to both generalization capability and prediction accuracy. To give insight into the black-box machine learning models, we also studied two kinds of explainable techniques, namely SHAP and LIME, in this study. SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are well-established and reliable approaches for explaining model decision-making, particularly in the medical industry. The findings of the experiment revealed that more complicated models outperformed simpler ones, with the top model obtaining almost 91% accuracy and the other models achieving 83-91% accuracy. The proposed framework, which includes global and local explainable methodologies, can aid in standardizing complicated models and gaining insight into their decision-making, which can enhance stroke care and treatment.

Keywords: Stroke, medical disorder, blood flow, neurological impairment, prediction algorithms, early intervention, machine learning (ML), stroke prediction, class imbalance.

1.INTRODUCTION

The incidence of stroke has been increasing globally, and it is now considered one of the leading causes of death and disability. Early intervention is crucial in preventing long term disability and mortality associated with stroke. Traditional methods of predicting stroke risk, however, are often time-consuming and prone to errors. Recently, machine learning algorithms have shown great promise in accurately predicting stroke risk based on various clinical risk factors.By leveraging these algorithms, clinicians can identify high-risk patients and intervene early, potentially reducing the number of stroke-related complications and improving patient outcomes. Additionally,there is a growing need for tranparency and explainability in machine learning models in healthcare. The use of interpretable machine learning model can provide clinicians with valuable insights into the factors that contribute to a patient's stroke risk, thereby aiding in treatment decisions. The World Stroke Organisation estimates that 13 million people worldwide experience a stroke each year, leading to 5.5 million fatalities [1]. Stroke affects all aspects of a patient's life, including their family, social environment, and work, and is one of the top causes of mortality and disability in the world [1, 2]. A common misconception is that certain groups of people, such as the elderly or those with underlying illnesses, are the only ones who are affected by stroke. In reality, anybody can be impacted, regardless of age, gender, or physical health [1, 2]. A stroke is a rapid, serious disruption in blood flow to the brain that deprives brain cells of oxygen. It comes in ischemic and haemorrhagic varieties. Moderate to severe strokes can cause permanent or temporary damage, depending on their severity.

Haemorrhagic strokes are uncommon; however, they are brought on by the rupture of a blood vessel in the brain. The most common type of stroke happens when an artery is blocked or narrows, preventing blood flow to the brain [3, 4]. Age over 55, prior stroke or TIA, arrhythmia, high blood pressure, carotid stenosis from atherosclerosis, smoking, high blood cholesterol, diabetes, obesity, inactivity, estrogenic therapy, blood clotting disorders, cocaine or amphetamine use, and heart issues like infarction and cardiac arrest are all risk factors for stroke [5-7]. Strokes can occur suddenly, and their symptoms might vary and be unanticipated. The main symptoms of a stroke include paralysis on one side of the body, numbness in the face, arms, or legs, difficulty speaking or walking, dizziness, blurred vision, headache, vomiting, drooping mouth, and, in severe cases, loss of consciousness and coma. These sensations may come on suddenly or gradually, and in certain rare cases, they may cause you to become aware [8–10]. Stroke can impact both men and women, lowering their quality of life and putting a load on public health resources. The scientific community prioritizes building models for predicting strokes to avoid them, and AI plays a critical role in this endeavour because it is extensively employed for disease prevention. Several research has been carried out to construct models for stroke diagnosis [11-13], predict treatment results and patient responses, and design individualized rehabilitation techniques [14-16]. Arslan et al. [17], for example, suggested a data mining system to predict ischemic strokes utilizing data from 80 ischemic stroke patients and 112 healthy persons, with the Support Vector Machine (SVM) classifier achieving the greatest accuracy of 97.89% and AUC of 97.83%. The study also looked at how different factors affected identifying the key risk factors for ischemic stroke.

2. LITERATURE SURVEY

[1] World Stroke Organization (WSO): Global Stroke Fact Sheet 2022

Stroke remains the second-leading cause of death and the third-leading cause of death and disability combined (as expressed by disability-adjusted life-years lost - DALYs) in the world. The estimated global cost of stroke is over US$721 billion (0.66% of the global GDP). From 1990 to 2019, the burden (in terms of the absolute number of cases) increased substantially (70.0% increase in incident strokes, 43.0% deaths from stroke, 102.0% prevalent strokes, and 143.0% DALYs), with the bulk of the global stroke burden (86.0% of deaths and 89.0% of DALYs) residing in lower-income and lower-middle-income countries (LMIC). This World Stroke Organisation (WSO) Global Stroke Fact Sheet 2022 provides the most updated information that can be used to inform communication with all internal and external stakeholders; all statistics have been reviewed and approved for use by the WSO Executive Committee as well as leaders from the Global Burden of Disease research group

[2] The relationship between social support and participation in stroke: A systematic review

Background: The incidence of cerebrovascular accidents with its devastating effects on individuals is increasing. Post-stroke, restrictions in participation are common and social support could have an influence on this. Social support provided to individuals post-stroke is vital, but the relationship between social support and participation is not well understood.Objectives: This review aimed to systematically determine the relationship between social support and participation post-stroke, based on the literature available.Method: Ebscohost, Science Direct, Biomed Central, Cochrane Library, Google Scholar, Pedro Central and Wiley Online were the electronic databases searched between 2001 and 2016. Articles were deemed to be eligible if they met the inclusion criteria and successfully underwent scrutiny to determine their relevance and methodological quality, using tools from the Critical Appraisal Skills Programme and Milton Keynes Primary Trust. A narrative synthesis method was used to analyse the included studies.Results: A total of 54 articles were identified after screening, and six articles were deemed eligible for inclusion. The articles consisted of cross-sectional, qualitative and cohort studies. Articles showed distinct, significant relationships between social support and participation where the quality and quantity of social support were important. High levels of social support had a positive influence on participation, social and leisure activities, as well as returning to work post-stroke.**Conclusion:** A positive relationship exists between social support and participation post-stroke. Health professionals need to include social support interventions when attempting to manage the individual with stroke holistically, as this will have positive effects on participation.

[3] Global Burden of Stroke

Stroke is the second leading cause of death and a major cause of disability worldwide. Its incidence is increasing because the population ages. In addition, more young people are affected by stroke in low- and middle-income countries. Ischemic stroke is more frequent but haemorrhagic stroke is responsible for more deaths and disability-adjusted life-years lost. Incidence and mortality of stroke differ between countries, geographical regions, and ethnic groups. In high-income countries mainly, improvements in prevention, acute treatment, and neurorehabilitation have led to a substantial decrease in the burden of stroke over the past 30 years. This article reviews the epidemiological and clinical data concerning stroke incidence and burden around the globe.

[4] Blood Biomarkers to Differentiate Ischemic and Hemorrhagic Strokes

Objective: To validate a panel of blood biomarkers to differentiate between ischemic stroke (IS) and intracerebral hemorrhage (ICH) in patients with suspected stroke.Methods: Patients with suspected stroke admitted within 4.5 hours after onset were enrolled. Blood samples were collected at hospital admission. Glial fibrillary acid protein (GFAP), retinol binding protein 4 (RBP-4), N-terminal proB-type natriuretic peptide (NT-proBNP), and endostatin were measured by immunoassays. Cutoff points were obtained for 100% specificity for IS. A high-sensitivity assay to measure GFAP and rapid point-of-care tests (POCTs) to measure RBP-4 and NT-proBNP were used in subsets of patients. Biomarker panels were evaluated in another cohort of 62 stroke mimics.Results: A total of 189 patients (154 IS and 35 ICH) were enrolled. Patients with IS had higher RBP-4, NT-proBNP, and endostatin and lower GFAP levels than patients with ICH. The best biomarker combination for the identification of IS was RBP-4+NT-proBNP, which was able to identify 29.7% of patients with IS with 100% specificity. In the subset of patients for whom GFAP was measured with the high-sensitivity assay, RBP-4, NT-proBNP, and GFAP identified 51.5% of patients with IS with 100% specificity. When stroke mimics were included, specificities were reduced to 98.4 and 96.8%, respectively. POCTs of RBP-4 and NT-proBNP showed results similar results to those of conventional ELISAs.Conclusions: A biomarker panel including RBP-4, NT-proBNP, and GFAP provided moderate but potentially useful sensitivity rates at 100% specificity for IS diagnosis. If confirmed in future studies, this strategy might allow prehospital treatment in selected patients.Classification of evidence: This study provides Class I evidence that a biomarker panel including RBP-4, NT-proBNP, and GFAP distinguishes IS from ICH with moderate accuracy.

[5] Prevalence and risk factors of stroke in the elderly in Northern China: data from the National Stroke Screening Survey

Background: The overall global burden of stroke is considerable and increasing. In China, stroke is the leading cause of death and disability.Methods: For this study, we used data from the National Stroke Screening Survey in 2012 and the 2010 Chinese population from sixth National Census of Populations to calculate a standardized (by age, gender, and education) stroke prevalence. Prevalence, risk factors, and management of stroke were compared by gender, age, and site.Findings: The standardized prevalence rate of survival stroke patients in study population aged 60 and older was 4.94% in total. Hypertension was the most prevalent risk factor for stroke. Compared to men, women were more likely to have diabetes, obesity, elevated low-density lipoprotein cholesterol (LDL-C), and atrial fibrillation ($P < 0.05$). Men were far more likely to drink and smoke than women ($P < 0.05$). The rates of diabetes and atrial fibrillation were substantially higher in urban than those in rural stroke survivors ($P < 0.05$). Rural stroke survivors exhibited higher rates of smoking and alcohol consumption than urban stroke survivors ($P < 0.05$).Interpretation: The stroke prevalence in China is in line with median worldwide stroke prevalence. Traditional risk factors remain highly prevalent in stroke survivors, among which hypertension was the most common. Stroke prevalence rates and risk factors varied by age, sex, and sociogeological factors.

[6] Hypertension and Diabetes Mellitus as a Predictive Risk Factors for Stroke

Background Stroke is becoming a major challenge in healthcare systems, and this has necessitated the study of the various risk factors. As the number of people with hypertension, diabetes mellitus and obesity increases, the problem is expected to worsen. This review paper evaluates what can be done to eliminate or reduce the risk of stroke. Objective The aim of the research is to evaluate the risk factors for stroke. The paper also aims to understand how these risks can be handled to avoid incidences of stroke. Method Published clinical trials of stroke risk factors studies were recognised by a search of EMBASE and MEDLINE databases with keywords hypertension, blood pressure, diabetes mellitus, stroke or cardiovascular disease, or prospective study, and meta-analysis. Results The findings of this review are that the prevention of stroke starts with identifying risk factors for stroke, most of the patients diagnosed with stroke have various risk factors. Consequently, it is a very significant to identify all the risk factors for stroke as well as to teach the patient how to dominate them. Conclusion after summarising all the studies mentioned in the paper, it can be established that hypertension and diabetes mellitus are a stroke risk factors and correlated in patients with atherosclerosis. Keywords: Hypertension; diabetes mellitus; stroke; risk factors; lifestyle.

[7] Stroke Risk Factors, Genetics, and Prevention

Stroke is a heterogeneous syndrome, and determining risk factors and treatment depends on the specific pathogenesis of stroke. Risk factors for stroke can be categorized as modifiable and nonmodifiable. Age, sex, and race/ethnicity are nonmodifiable risk factors for both ischemic and hemorrhagic stroke, while hypertension, smoking, diet, and physical inactivity are among some of the more commonly reported modifiable risk factors. More recently described risk factors and triggers of stroke include inflammatory disorders, infection, pollution, and cardiac atrial disorders independent of atrial fibrillation. Single-gene disorders may cause rare, hereditary disorders for which stroke is a primary manifestation. Recent research also suggests that common and rare genetic polymorphisms can influence risk of more common causes of stroke, due to both other risk factors and specific stroke mechanisms, such as atrial fibrillation. Genetic factors, particularly those with environmental interactions, may be more modifiable than previously recognized. Stroke prevention has generally focused on modifiable risk factors. Lifestyle and behavioral modification, such as dietary changes or smoking cessation, not only reduces stroke risk, but also reduces the risk of other cardiovascular diseases. Other prevention strategies include identifying and treating medical conditions, such as hypertension and diabetes, that increase stroke risk. Recent research into risk factors and genetics of stroke has not only identified those at risk for stroke but also identified ways to target at-risk populations for stroke prevention.

[8] Stroke symptoms and the decision to call for an ambulance

Background and purpose: Few acute stroke patients are treated with alteplase, partly because of significant prehospital delays after symptom onset. The aim of this study was to determine among ambulance-transported stroke patients factors associated with stroke recognition and factors associated with a call for ambulance assistance within 1 hour from symptom onset.Methods: For 6 months in 2004, all ambulance-transported stroke or transient ischemic attack patients arriving from a geographically defined region in Melbourne (Australia) to 1 of 3 hospital emergency departments were assessed. Tapes of the call for ambulance assistance were analyzed and the patient and the caller were interviewed.Results: One hundred ninety-eight patients were included in the study. Stroke was reported as the problem in 44% of ambulance calls. Unprompted stroke recognition was independently associated with facial droop ($P=0.015$) and a history of stroke or transient ischemic attack ($P<0.001$). More than half of the calls for ambulance assistance were made within 1 hour from symptom onset and only 43% of these callers spontaneously identified the problem as "stroke." Factors independently associated with a call within 1 hour were: speech problems ($P=0.009$), caller family history of stroke ($P=0.017$), and the patient was not alone at symptom onset ($P=0.018$).Conclusions: Stroke was reported as the problem (unprompted) by <50% of callers. Fewer than half the calls were made within 1 hour from symptom onset. Interventions are needed to more strongly link stroke recognition to immediate action and increase the number of stroke patients eligible for acute treatment.

[9] Response to symptoms of stroke in the UK: a systematic review

BackgroundThe English National Stroke Strategy suggests that there is a need to improve the response of patients and witnesses to the symptoms of acute stroke to increase rapid access to specialist care. We wished to review the evidence base regarding the knowledge, attitudes and behaviours of stroke patients, witnesses and the public to the symptoms of stroke and the need for an urgent response at the onset of symptoms.MethodsWe conducted a systematic review of UK articles reporting empirical research on a) awareness of and response to the symptoms of acute stroke or TIA, and b) beliefs and attitudes about diagnosis, early treatment and consequences of acute stroke or TIA. Nine electronic databases were searched using a robust search strategy. Citations and abstracts were screened independently by two reviewers. Data were extracted by two researchers independently using agreed criteria.Results11 studies out of 7144 citations met the inclusion criteria. Methods of data collection included: postal survey (n = 2); interview survey (n = 6); review of hospital documentation (n = 2) and qualitative interviews (n = 1). Limited data reveal a good level of knowledge of the two commonest stroke symptoms (unilateral weakness and speech disturbance), and of the need for an emergency response among the general public and at risk patients. Despite this, less than half of patients recognised they had suffered a stroke. Symptom recognition did not reduce time to presentation. For the majority, the first point of contact for medical assistance was a general practitioner.ConclusionsThere is an assumption that, in the UK, public knowledge of the symptoms of stroke and of the need for an emergency response is lacking, but there is little published research to support this. Public awareness raising campaigns to improve response to the symptoms of stroke therefore may not produce an increase in desired behaviours. Further research is needed to understand why people who experience or witness stroke symptoms frequently do not call emergency services.

[10] The differential diagnosis of suspected stroke: a systematic review

Background: We aimed to determine the proportion of patients who had suffered a stroke and compare this to those patients with suspected stroke, and the range of differential diagnosis for suspected stroke.Methods: We searched for prospective studies of suspected stroke in electronic databases and our personal files. We undertook a meta-analysis of these studies, aimed at determining the proportions of patients with confirmed stroke in different settings.**Results:** We identified 29 studies involving 8,839 patients: 13 studies were from emergency departments, five from stroke units or transient ischaemic attack (TIA) clinics, three from primary care, three from ambulance services and five were unspecified. About three-quarters (74% [95% confidence interval (CI): 66 to 83%]) of patients had a diagnosis of stroke, though there was significant heterogeneity in this estimate. The five most frequent non-stroke diagnoses were seizure, syncope, sepsis, migraine and brain tumours.**Conclusion:** Patients who had not had a stroke accounted for a significant proportion of people referred to stroke services. Expertise in the differential diagnoses of stroke is needed in order to manage the patients at the point of referral.

3. PROPOSED METHODOLOGY

The proposed work focuses on developing an automated stroke prediction model by leveraging advanced data preprocessing techniques and multiple machine learning algorithms to ensure high accuracy and reliability. Initially, missing values in the dataset are handled through removal or imputation to maintain data integrity. Since stroke datasets often suffer from class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to generate synthetic samples for underrepresented stroke cases, thereby improving the model's ability to detect actual stroke occurrences. To enhance model efficiency, feature selection is performed using the CHI-Square (CHI2) algorithm, which identifies the most significant predictors of stroke risk, reducing computational complexity and improving performance. The processed dataset is then trained on six machine learning algorithms, including Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression (LR), Extreme Gradient Boosting (XGBoost), and Naïve Bayes (NB). Among these models, Random Forest demonstrates the highest accuracy, making it the most reliable for stroke prediction. The models are evaluated using key performance metrics such as accuracy, precision, recall, and F1-score, ensuring a comprehensive assessment of their predictive capabilities. By integrating data preprocessing, feature selection, and performance evaluation, this methodology enhances stroke prediction accuracy, making it a valuable tool for early intervention and risk assessment in healthcare. Additionally, Explainable AI (XAI) techniques can be incorporated to provide transparent and interpretable predictions, aiding clinicians in makinginformed decisions.

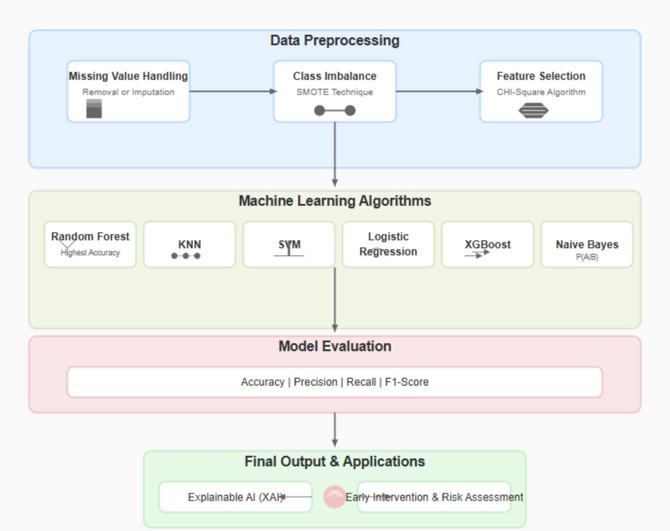

Figure 1: Automated Stroke Prediction Model Workflow

The proposed methodology typically includes the following key components:

1. Data Preprocessing

Imbalance Data Handling Using SMOTE: Since stroke datasets often have an imbalanced class distribution (with fewer stroke cases compared to non-stroke cases), the Synthetic Minority Over-sampling Technique (SMOTE) is applied to balance the dataset.

Feature Selection Using CHI-Square (CHI2) Algorithm: The CHI2 statistical test is employed to select the most relevant features that contribute significantly to stroke prediction. This helps in reducing model complexity and improving computational efficiency.

2. Model Training and Evaluation

The processed dataset is trained using five different machine learning algorithms to compare their performance:

- Random Forest (RF)
- K-Nearest Neighbors (KNN)
- Support Vector Machine (SVM)
- Logistic Regression (LR)
- Extreme Gradient Boosting (XGBoost)

Among these models, Random Forest achieves the highest accuracy, making it the best-performing model for stroke prediction.

Each model's performance is evaluated using four key metrics:

Accuracy: Measures overall correctness of predictions.

Precision: Determines how many of the positive predictions were actually correct.

Recall (Sensitivity): Assesses how well the model identifies actual stroke cases.

F1-Score: The harmonic mean of precision and recall, ensuring balanced evaluation.

3. Explainable AI (XAI) for Model Transparency

The model integrates Explainable AI (XAI) techniques such as SHAP (SHapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) to provide interpretable insights into stroke prediction.

These techniques help clinicians understand which features contribute the most to a patient's stroke risk, enhancing trust and usability.

4. Web-Based Application for Real-Time Stroke RiskPrediction

A user-friendly web application is developed to enable healthcare professionals and individuals to input patient data and receive instant stroke risk predictions.

The system processes the input through the trained model and provides explainable insights for decision-making.

Applications:

1. **Early Stroke Detection & Prevention**

Helps doctors assess stroke risk at an early stage, allowing preventive interventions before an actual stroke occurs.

2.Clinical Decision Support System (CDSS)

Assists healthcare professionals by providing data-driven stroke risk predictions and insights, enhancing evidence-based treatment plans.

3.Personalized Healthcare

Patients can track their stroke risk based on their lifestyle and clinical factors, enabling personalized recommendations for lifestyle modifications.

4.Medical Research and Data Analysis

Helps researchers understand patterns and risk factors for stroke by analyzing large datasets, leading to better prevention strategies.Y6

5. Public Health and Epidemiology

Useful for large-scale screening of populations at risk, contributing to public health initiatives aimed at reducing stroke incidence.

Advantages:

1. **High Prediction Accuracy**

The Random Forest model outperforms other algorithms, ensuring more reliable predictions.

2. **Effective Handling of Imbalanced Data**

SMOTE enhances model performance by ensuring both stroke and non-stroke cases are adequately represented.

3. **Feature Selection for Improved Efficiency**

CHI2 feature selection ensures that only the most relevant features are used, reducing model complexity and improving computational efficiency.

4. Transparent and Explainable Predictions

Integration of Explainable AI (XAI) techniques providesinterpretability, ensuring that healthcare professionals can trust and understand the model's decisions.

5. Real-Time Stroke Risk Prediction

The web application enables instant stroke risk assessment, making it practical for real-world clinical use.

6. Scalability and Flexibility

The methodology can be scaled to other healthcare applications, such as heart disease prediction, diabetes risk assessment, and general patient monitoring.

4. EXPERIMENTAL ANALYSIS

Stroke often causes due to blood flow stop to brain and this is one of the deadly diseases. Patient life can be saved and stroke can be avoided by timely and accurate detection. Existing detection technique requires heavy resources and they make time for prediction. All this processed features will get trained on 6 different algorithms such as Random Forest, KNN, SVM, Logistic Regression, XGBOOST and Naive Bayes. In all algorithm Random Forest is giving high accuracy and each algorithm performance is evaluated in terms of accuracy, precision, recall and FSCORE.

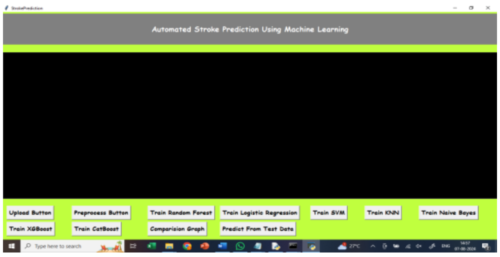

Figure 2: Sample Image

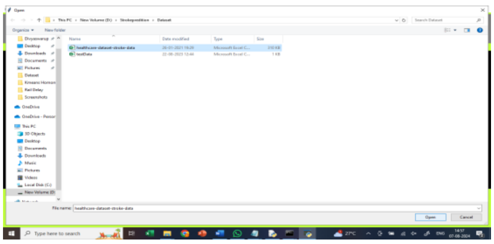

Figure 3: Healthcare Dataset

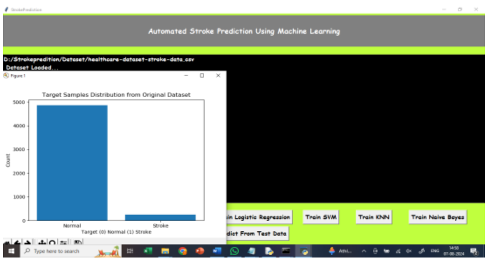

Figure 4: Stroke Dataset

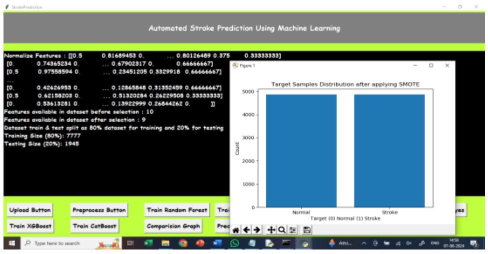

Figure 5: Preprocessed Data

Figure 6 : Random Forest Confusion Forest

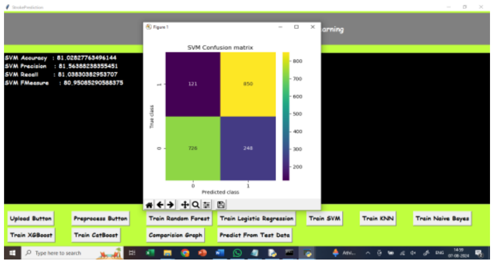

Figure 7 : SVM Confusion Matrix

Figure 8 : XG Boost Confusion Matrix

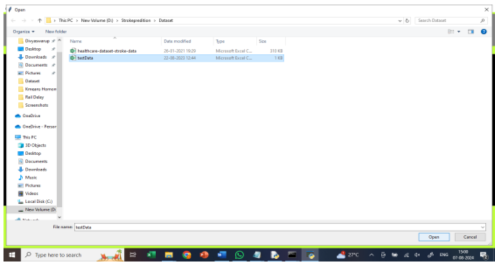

Figure 9 : Prediction Using Test Data

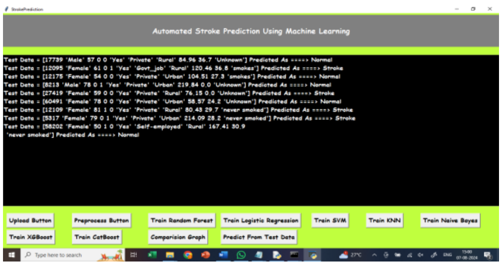

Figure 10 : Stroke Result

5. CONCLUSION

As an interdisciplinary course, Machine Vision combines AI and digital image processing methods. This paper develops a comprehensive experiment on forest wildfire detection that organically integrates digital image processing, machine learning and deep learning technologies. With the rapid development of computer technology and the popularity of cameras, machine vision technology based on artificial intelligence (AI) and digital image processing has been applied to increasing fields, such as face detection , wildfire detection, object measurement and surface defect detection. As an interdisciplinary course, Machine Vision combines AI and digital image processing. With the development of AI, machine vision can replace human beings with intelligent programs for some automated operations and measurements.

A complete machine vision system includes a camera and an image processing device. The associate editor coordinating the review of this manuscript and approving it for publication was Senthil Kumar . The camera firstly obtains the images, then we can recognize the target object through the computer's visual recognition algorithm, and finally the image processing device can output the target recognition result through the terminal. At present, machine vision has become one of the essential skills of image and video processing practitioners, and is also an important professional course in intelligent manufacturing, computer science and technology, and other majors. With the rapid development of AI in recent years, there is an increasing demand for talents in two main application fields, natural language processing and digital image processing.

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