Prediction of Stroke Risk Using a Hybrid Deep Transfer Learning Framework

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ABSTRACT

Stroke has become the world's leading cause of death and long-term disability, with no effective treatment. Deep learning-based approaches may outperform existing stroke risk prediction models, but they require large amounts of well-labeled data. Stroke data is typically distributed in small pieces among different hospitals due to the strict privacy protection policy in health-care systems. The positive and negative examples of such data are extremely skewed. Transfer learning can solve small data issues by leveraging knowledge from a related domain, especially when multiple data sources are available. We propose a novel Hybrid Deep Transfer Learning-based Stroke Risk Prediction (HDTL-SRP) scheme to exploit the knowledge structure from multiple correlated sources (i.e., external stroke data, chronic diseases data, such as hypertension and diabetes) in this paper.The proposed framework has been thoroughly tested in both simulated and real-world scenarios.

1.INTRODUCTUION

Stroke is the subsequent driving reason for death overall and one of the most dangerous infections for people over 65 years. Like a "heart attack," which damages the heart, it affects the brain. Once a stroke disease occurs, it can eventually result in death as well as enormous costs for medical care and permanent disability. Like clockwork somebody passes on from stroke, yet up to 80% of stroke can be forestalled on the off chance that we can recognize or foresee the event of stroke in its beginning phase.

Stroke is a blood coagulation or drain in the mind which can make long-lasting harm that meaningfully affects versatility, perception, sight or correspondence. A stroke is a medical emergency that can result in long-term neurological damage, complications, and frequently death. The majority of strokes are categorized as hemorrhagic and ischemic embolic. When a blood clot forms away from the patient's brain, typically in the patient's heart, it travels through the patient's bloodstream to

lodge in narrower brain arteries, causing an ischemic embolic stroke. Another kind of brain stroke is hemorrhagic stroke, which occurs when an artery in the brain bursts or leaks blood.

Although many of the diseases that precede strokes take a long time to develop, strokes occur suddenly. For this reason age is the most obvious gamble factor for stroke: the opportunity of blockage or breakage ascends as time passes, so - despite the fact that it can strike at whatever stage in life - stroke is substantially more logical the more seasoned we get.

Age, systolic blood pressure, body mass index (BMI), cholesterol, diabetes, smoking status and intensity, physical activity, alcohol consumption, and previous history (hypertension, coronary heart disease) are included in the stroke risk factors in the profile. Stroke risk can be estimated based on the profile's risk factors, which can be easily determined during a routine physical examination in a doctor's office. A singular's gamble can be connected with the typical gamble of stroke for people of a similar age and sex

2.LITERATURE SURVEY

2.1 Burden of Stroke in the World

Stroke is the second leading cause of death and leading cause of adult disability worldwide with 400-800 strokes per 100,000, 15 million new acute strokes every year, 28,500,000 disability adjusted life-years and 28-30-day case fatality ranging from 17% to 35%. The burden of stroke will likely worsen with stroke and heart disease related deaths projected to increase to five million in 2020, compared to three million in 1998. This will be a result of continuing health and demographic transition resulting in increase in vascular disease risk factors and population of the elderly. Developing countries account for 85% of the global deaths from stroke. The social and economic consequences of stroke are substantial. The cost of stroke for the year 2002 was estimated to be as high as $49.4 billion in the United States of America (USA), while costs after discharge were estimated to amount to 2.9 billion Euros in France.

2.2 Burden of Stroke in Africa

A systematic review of the existing literature to examine the burden and profile of stroke in the WHO African region reported an annual incidence rate of stroke of up to 316 per 100,000, a prevalence rate of 315 per 100,000 and a three-year fatality of up to 84% in Africa. Disabling stroke prevalence may be at least as high as in high-income areas. In

2002, model-based estimated age-adjusted stroke mortality rates ranged between 168 and
179 per 100,000 population for countries in the African region. Case–fatality data available from three hospital based urban stroke registers in South Africa (two South African and one from Zimbabwe) found 30 day case fatality ranging between 33 and35%. Given the economic burden of stroke in the developed countries, a small fraction of such amounts can cause enormous economic damage to low income countries especially in SSA, given the younger age at which stroke occurs. A study done in Togo estimated direct cost per person of 936 Euros in only 17 days, about 170 times more than the average annual health spending of a Togolese.

2.3 Burden of Stroke in Uganda

The actual burden of stroke in Uganda is not known. According to WHO estimates for heart disease and stroke 2002, stroke was responsible for 11 per 1000 population (25,004,000) 4 disability adjusted life years and mortality of 11,043. Stroke is one of the common neurological diseases among patients admitted to the neurology ward at Mulago, Uganda's national referral hospital accounting for 21% of all neurological admissions. Unpublished research done at Mulago hospital, showed a 30-day case fatality of 43.8% among 133 patients admitted with stroke. The economic burden caused by stroke has not been explored in Uganda but given the very high dependent population (53%), high prevalence of HIV/AIDS, drug resistant TB and Malaria, the impact of stroke and other emerging non-communicable diseases on the resource limited economy is astronomical.

3.PROPOSED WORK

We propose a novel Hybrid Deep Transfer Learning-based Stroke Risk Prediction (HDTL-SRP) scheme to exploit the knowledge structure from multiple correlated sources (i.e., external stroke data, chronic diseases data, such as hypertension and diabetes) in this paper.The proposed framework has been thoroughly tested in both simulated and real-world scenarios

In the United States, approximately 795,000 people have a new or recurring stroke each year. In the United States, someone has a stroke every 40 seconds, and someone dies from a stroke every 4 minutes. Stroke is the fifth leading cause of death and the leading cause of disability in the United States. Most strokes are preventable, and if treated promptly, the chances of a good outcome after a stroke can be greatly improved..

An ischemic stroke, also known as a cerebral infarction, is the most common type of stroke. A blood vessel supplying oxygen and nutrients to the brain becomes blocked, resulting in the death of brain cells. Because these cells cannot be replaced, the damage is permanent. However, because the brain can adapt, many patients improve, and some are not permanently disabled. A cerebral haemorrhage occurs when a blood vessel in the brain ruptures, resulting in bleeding and damage to brain tissue.

High blood pressure, also known as hypertension, is the most significant risk factor for both types of stroke. Diabetes, an irregular heart rhythm known as atrial fibrillation, high cholesterol, smoking, physical inactivity, a family history of stroke, and chronic kidney disease are all common risk factors for stroke. Thus, predicting the likelihood of a stroke based on these risk factors may save many lives.

3.1 IMPLEMENTATION

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Bayesian Optimization for Network Parameter Selection While multiple source domains are available in the network weight transfer approach, parameters such as the number of transferred layers and the transferred sequence of different source domains are important factors in SRP model performance. To build the best SRP model with n related source domains available, as shown in Fig 3, we must identify the parameters that optimise model performance, such as the transferred layer number of the i-th source domain Si and the transferred sequence. The transferred layer number and sequence of the i-th source domain Si should be evaluated. Traditionally, in order to find the best parameters, all parameters must be evaluated, which takes time. To address this issue, Gaussian process-based Bayesian Optimization approach (BO) is used to get the optimal parameters quickly. We use Levenshtein Distance (LD) to get the similarity of different transfer sequence. Then, Multiple Dimensional Scaling (MDS) algorithm is used to get low dimension search space for BO

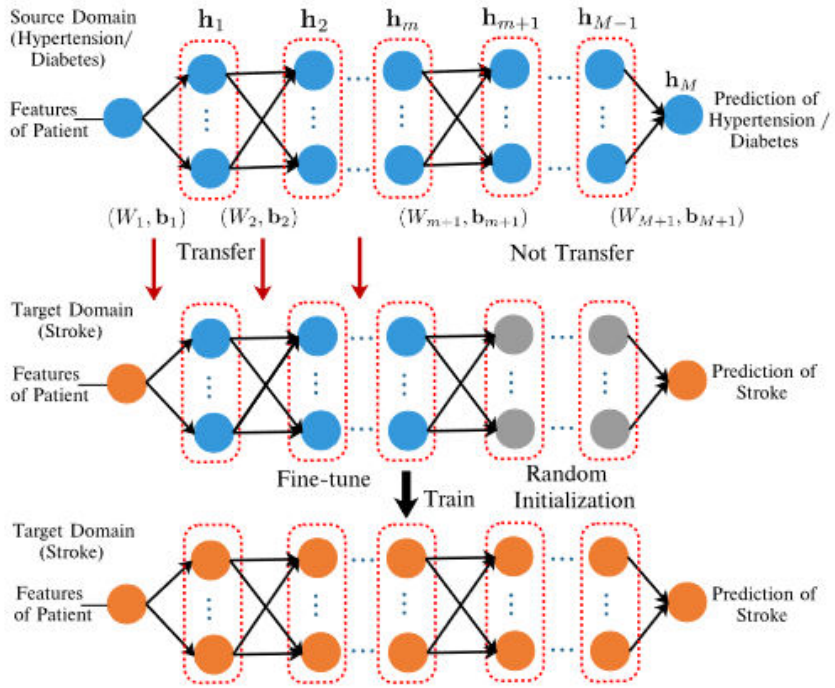
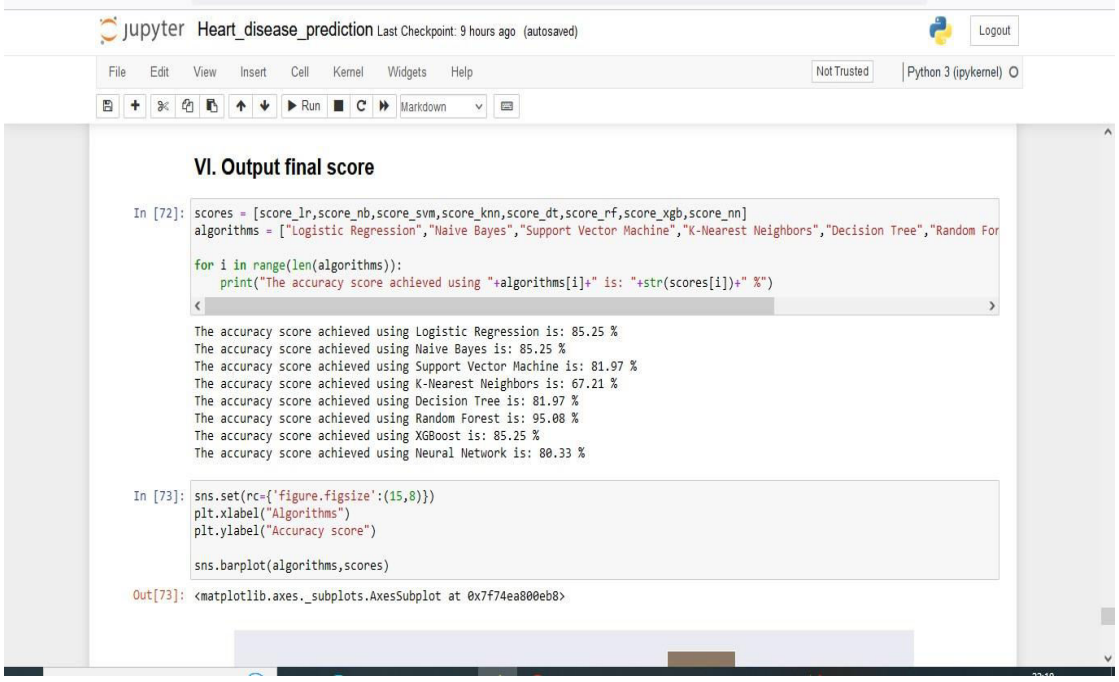
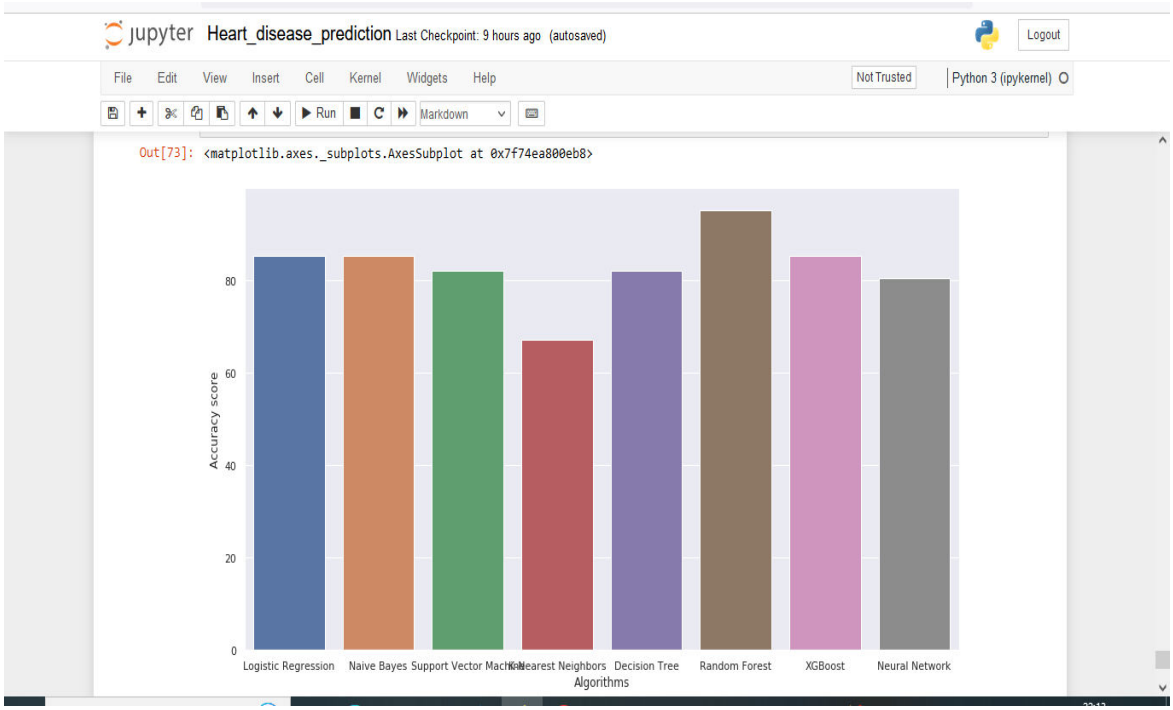


Fig 1:

4.RESULTS AND DISCUSSION





5.CONCLUSION

Several assessments and prediction models, including Decision Tree, Naive Bayes, and Neural Network, performed well in identifying stroke-prone patients. As a result, this project assists in predicting stroke risk using a prediction model and providing personalized warnings and lifestyle correction messages via a web application. By doing so, it encourages medical users to increase their motivation for health management and to change their health behaviours..

6. FUTURE SCOPE

This project uses a prediction model to predict stroke risk in older people and people who are addicted to the risk factors mentioned in the project.

In the future, the same project can be extended to provide the stroke percentage based on the current project's output. This project can also be used to determine stroke probabilities in young and underage people by collecting risk factor information and consulting doctors

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