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Cloud-Enhanced Prediction of Stroke Outcomes Using Spiking Neural Networks

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Abstract

Stroke is one of the major causes of mortality and disability worldwide, thus inducing the importance of accurately predicting risk and aiding early intervention therapies. Conventional methods of predicting risk for stroke are clinical evaluations, demographic factors, and the presence of any signs and symptoms; but these methods definitely fail to assess the dynamic interactions among risk factors with each other toward stroke. In this paper, we propose Spiking Neural Networks with cloud computing to improve both predictive accuracy and scalability of stroke predictive models. This is further enhanced by integrating an advanced Symptom Severity Scoring and Target Encoding approach to deliver reliable assessments of risk for stroke. Cloud technology can do this effectively in processing and storing huge piles of datasets that could very well be updated and applied easier across health systems. It would thus pave ways towards better-optimized, efficient, and reliable predictive tools against strokes, which would eventually improve clinical decision-making and patient outcomes.

Keywords: Stroke Prediction, Spiking Neural Networks, Cloud Computing, Symptom Severity Scoring, Target Encoding, Healthcare Data Analysis

1. INTRODUCTION

Stroke, one of the major contributors to mortality and long-term disability, affects millions of people every year globally [1]. The early prediction of stroke risk may really reduce the detriment inflicted by stroke upon individuals and healthcare systems [2]. Traditional stroke risk determinants would include clinical assessment, demography, and the presence of symptoms [3]. Some of these may fall into the objective realm, are definitely time-consuming, and still may not be able to grasp the complex multifactorial reality of stroke risk [4]. With recent advances in machine learning and artificial intelligence (AI) applications, new avenues are opening for stroke prediction through the analysis of huge amounts of healthcare data [5]. Of the many techniques, Spiking Neural Networks that are biomimetic of biological neuron dynamics hold great promise in dealing with the temporal and hierarchical structure of data typical of medical diagnoses [6]. SNNs can provide a time-continuous processing of signals from patients, thus making it a good candidate in the prediction of stroke events where the temporal evolution of symptoms is critical [7]. These sophisticated techniques can potentially bring about a drastic improvement in the accuracy and trustworthiness of stroke risk prediction outcomes, thus benefiting both health professionals and patients along their treatments [8]. A new means to synchronize the dynamic attributes of neurons with medical data analysis is offered by this model [9].

Spiking Neural Networks (SNNs) are highly efficient in capturing the sequential nature of patient data, which makes them a promising frontage for predicting strokes [10]. One great thing SNNs have going for them is that it is capable to model the chronology and patterns in the data, which is essential in comprehending the jeopardy of stroke advancement over time [11]. With a scan of infodump in the process, these neural networks work on a spiking input pattern, like biological neurons, which rings as an added advantage in real-time data flows [12]. The increasing volume of data generation by healthcare systems, highly countenances scalable AI solutions to manage and analyse that data efficiently [13]. These quandaries are aggrandized by the Eleventh Article of the Research Worthiness of Shao Cheng Cloud Computing, which springs scalability and enhanced processor power for bulk data sets [14]. In other words, the integration of SNNs with cloud computing allows training and deployment of stroke prediction models with huge amounts of patient data without any on-site infrastructure [15]. This fusion blinds the degradation of its role in accuracy and efficiency of the models of predicting stroke [16]. Moreover, cloud computing proposes a landscape where the model updates with real-time patient data actually come in [17]. This keeps the model in touch with past trends in risk factor acquisition that need to be considered at every point [18]. Further, in the global paradigm, cloud platforms offer opportunities for models to be shared across different healthcare systems, hence enhancing collaborations that will enhance model accessibility [19]. The integration of AI and cloud computing provides opportunities for bringing these solutions into practical ways that extend to different healthcare settings acknowledged to be beneficial [20]. These are not just technological advances, but promises for creating more reliable and robust stroke prediction systems for clinicians [21]. Thus, the integration of Spiking Neural Networks into cloud infrastructure is potentially an upward curve toward building intelligent systems that contribute to improving patient outcomes [22]. This paper ultimately summarizes a broad sketch of the beneficial algorithms for risk prediction in assessment of stroke development to achieve on-time interventions and upscale quality healthcare provision [23].

PROBLEM STATEMENT

Stroke is a foremost cause of death and long-term disability, thus emphasizing the importance of predicting the risk of stroke in order to mitigate its consequences [24]. Traditional methods of stroke risk prediction are based on clinical assessments and demographic factors, yet these do a poor job of reflecting the complex and dynamic interrelationships of these risk factors and symptoms over time [25]. This paper highlights the limitations of the traditional approaches and advocates the integration of SNN with cloud computing to the outcome prediction of stroke cases [26]. Being a strong temporal data processing paradigm, SNNs would be well suited for modeling the ever-changing nature of stroke risk, while cloud computing would provide scalability and fast data processing [27]. In addition, features such as symptom severity scoring and target encoding could be employed to improve the accuracy and reliability of stroke predictions [28]. This would provide a stoic, scalable, and effective system for early intervention in improving the quality of medical decision-making [29].

Objective

- Using the Spiking Neural Network (SNN) to analyse dynamic relationships between risk factors and symptoms associated with stroke.
- Evaluate how cloud computing can facilitate increased scalability and computational efficiency for stroke prediction models.
- Improvement in stroke risk prediction accuracy through Symptom Severity Scoring and Target Encoding.
- Integrated with cutting-edge machine learning and cloud-based, big infrastructures for capacity dealing that are at their best for large and complex healthcare datasets.
- Very robust and scalable dedicated system for stroke predictions which can be deployed in various health care systems so as to ensure early intervention applications for better patient outcome.

2. LITERATURE SURVEY

Stroke prediction has been an area of extensive research, with various approaches exploring different machine learning models to assess stroke risk [30]. In modelling stroke prediction, traditional approaches mainly consider clinical judgment and demographic factors [31]. While these models showed reasonable performance in some scenarios, they are not able to account for the complex interplay that the various risk factors exert on the event of stroke [32]. Recent advances in stroke prediction accuracy and reliability include the use of such methods as decision trees, support vector machines, and neural networks [33]. These models generally operate under the assumption that large amounts of labelled data are available for training; in many health-care settings, such environments are sparse or imbalanced [34]. In addition to this, quite often, traditional machine learning models do not model sequential dependencies of patient data, which are crucial to predict events like strokes occurring over time [35].

Spiking Neural Networks [SNNs] are getting some recent attention since they are able to represent temporal data emulating the firing patterns of biological neurons [36]. SNNs can process sequential data that will help stroke prediction since these events can progress over time and hence indicate the probability of the occurrence of an event [37]. Unlike conventional neural networks, SNNs process information in the form of spikes. This captures the more dynamic nature of patient data [38]. Studies have shown that SNNs have advantages over conventional statistical learning in situations where the data involves sequential or temporal properties, such as speech recognition and image processing [39]. In this respect, SNNs are strong candidates for stroke prediction, for example, since timing and sequences of symptoms are important [40].

Capacity to manage and decode complex data is necessary for stroke prediction, and Feature Extraction indeed plays a central role in performance enhancement for AI models [41]. Although conventional feature selection methods such as Random Forest and Lasso Regression have been used to determine the most relevant features in stroke prediction, those measures might not be able to capture the convoluted relationships between symptoms over time [42]. Instead, the method of Symptom Severity Scoring, which compiles symptoms into a single composite feature, has been proven to enable additional improvement in predicting power of machine learning models as all the individual values of severity are brought into one number [43]. This will permit such models to give priorities to critical symptoms while eventually improving strokes prediction [44].

The most recent studies conducted in stroke prediction have also talked about data preprocessing techniques, which optimize the performance of the stroke prediction model [45]. Missing value operations in KNN imputation have proven to be the most complete filling of missing data by ensuring the integrity and completeness of the dataset [46]. Target Encoding also transformed the categorical features like presence or absence of symptoms into definitive numerical values that relate directly with stroke risk [47]. These preprocessing techniques are used to prepare the data for deep learning models so that the predictive system operates with very low data losses or bias [48].

The use of cloud-based computing in healthcare services has drastically improved the scalability and efficiency of stroke prediction models [49]. Cloud platforms provide the computing power necessary for the processing of large and high-dimensional datasets, thus enabling the training of more complex machine learning models. In addition, this technology allows easy model updates and retraining when new data is started to be captured, thereby ensuring continuous improvement of stroke prediction models. Besides, cloud-based solutions provide distributed computing, which will enhance efficiency by allowing training of models like SNNs across many servers, drastically cutting down the training time.

3. PROPOSED METHDOLOGY

A structured workflow diagram for a deep learning system for stroke prediction using a SNN. This starts from data collection, in which relevant data about patients collected. Then follows preprocessing-where techniques such as target encoding and missing value treatment, and so on, come to play in preparation of this data for analysis. Resulting from preprocessing, the extraction of features is carried out using the Symptom Severity Score, which creates a composite feature for the severity of symptoms. These extracted features are then used for classification through a SNN model. Cloud integration ensures that computational resources for training and deployment are optimally used. Finally, the effectiveness of the model is evaluated using performance metrics which can help assess the accuracy and reliability of predictions.

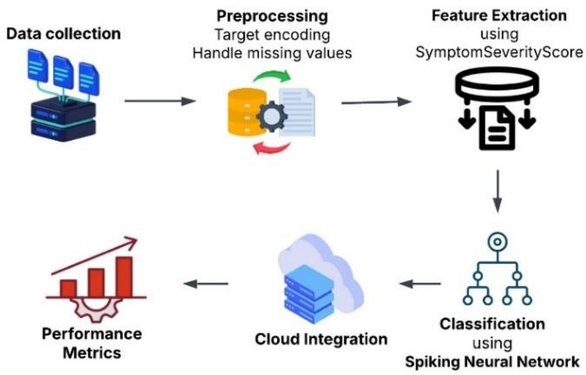

Figure 1:

3.1 DATA COLLECTION:

In your job, the activity of Data Collection means gathering complete patient information consisting of clinical symptoms and demographic factors to evaluate the risk for stroke. Normally, categorical symptoms like chest pain, dizziness, and shortness of breath, and continuous variables such as age and risk percentages for stroke are also used as items in the roster. This all plays a substantial role for the support in the construction of a really good predictive model-the ground upon which one would go analysing how some risk factors relate to stroke events in a given population. The collected data would have to be representative concerning the target population and not to be missed for anything like medical records or, better yet, health surveys or some diagnostic tests for clinical statement accurate prediction.

3.2 DATA PREPROCESSING

In the part of your job that is Data Preprocessing, it means preparing the gathered patient data for analysis by addressing common things such as missing values; outliers; categorical features. Missing values are handled through imputation techniques like KNN imputation or Deep Learning based imputation for making the dataset complete. They also normalized Age and potential stroke risk percentages within the Min-Max Scales in order to put them on a common scale. So preprocessing will make this data clean and consistent for feature extraction and model training, which ultimately will result in a better prediction of stroke risk.

3.2.1 Target Encoding:

Target Encoding helps achieve the ongoing conversion for categorical features like the presence or absence of symptoms into numerical representations of their relationship with the target variable in stroke disease risk. It computes the mean of the target [stroke risk] for each category of a certain feature and assigns it as the encoded value of that category. For example, for a binary symptom "chest pain" [1 = present, 0 = absent], the encoding would be the mean stroke risk of individuals with it versus those without it. Target encoding can be mathematically represented in eqn1:

$$\text{Encoded Value for Category } k = \frac{\sum_{i=1}^{N_k} Y_i}{N_k} \tag{1}$$

Where: Encoded Value for Category k is the mean stroke risk for category k of the categorical feature, N_k is the number of samples in category k, Y_i is the stroke risk of the i-th sample in category k.

3.2.2 Handle Missing Values:

Handling missing values is one of the relations in data preprocessing to ensure the data goes through just how much it can for model training. Missing data may occur for a number of reasons, whereby for instance, medical records may be incomplete or measurements may have been omitted. One of the ways to handle missing values is K-Nearest Neighbours Imputation; in this method, the missing value for a feature is substituted with the average value of its closest neighbours according to other available features. Missing value for a feature X_i might be imputed in eqn2:

$$X_i^{\text{imputed}} = \frac{1}{k} \sum_{j=1}^{k} X_j \tag{2}$$

Where: X_i^{imputed} is the imputed value for the missing data point i, k is the number of nearest neighbours considered for imputation, X_j is the value of the feature from the j-th nearest neighbour of i.

3.3 FEATURE EXTRACTION USING SYMPTOM SEVERITY SCORING

Feature Extraction with Symptom Severity Scoring entails the making of a composite feature which quantifies the degree of severity of a patient's symptoms itself, which is extremely critical in predicting the risk of stroke occurring in that person. Each symptom is given weight according to that one specific symptom's clinical importance or severity, and the resulting weighted values of the symptoms presented by the patient come to give the total severity score for an individual patient. For example, if during an evaluation, a patient produces both chest pain and dizziness, each would be given its relative weight and the overall severity score S total would be computed in eqn3:

$$S_{\text{total}} = \sum_{i=1}^{n} w_i \cdot x_i \tag{3}$$

Where: S_{total} is the total symptom severity score, w_i is the weight assigned to the i-th symptom based on its severity, x_i is the binary indicator [0 or 1] for the presence of the i-th symptom, n is the total number of symptoms.

3.4 CLASSIFICATION USING SPIKING NEURAL NETWORK

An illustration represents a SNN, built on a Winner-Take-All (WTA) network. Here, input neurons fire on receiving external stimuli, and the spikes thus generated travel to the excitatory neurons (Ex), propagating the activity further. All the while, the inhibitory neurons (Inh) control and suppress others so that the most activated neuron wins and becomes active under competition: This competitive mechanism embodies the WTA network, as the winner neuron is allowed to retain its activity, while all the other neurons are strongly inhibited in their activity levels.

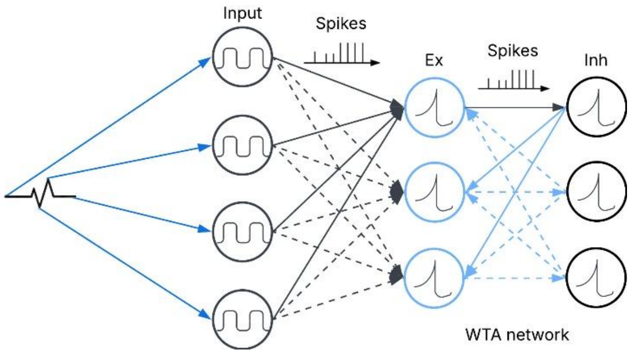

Figure 2: Spiking Neural Network

3.4.1 Input Neurons

The input neurons in a SNN are simply the first layer of neurons receiving external stimuli or incoming features such as patient symptoms or demographics. These neurons produce spikes: time-dependent signals that convey the information that is then transported through the network. The input signal is then converted to a spike train in which the firing rate of the neuron depends on the value of input. For example, symptom occurrence might be suggested with greater intensity or weight in spike frequency from a higher input. This relationship can then be mathematically represented in eqn4:

$$S(t) = \frac{1}{1+\exp\left(-w \cdot X)t\right))} \quad (4)$$

The spike train produced by the input neuron at time t is denoted by $S(t)$, The weight given to the input characteristic $X(t)$, which denotes the severity of the symptom [such as dizziness or chest discomfort], is w. The input feature at time t is represented by $X(t)$, where higher values produce more frequent spikes.

3.4.2Inhibitory Neurons

Within a SNN, inhibitory neurons are very important since they regulate the activity of the networks by inhibiting excitation firing from some other neurons. This will enforce a WTA mechanism where only the most relevant neuron or the strongest activated neuron would fire, and others are inhibited. These neurons actually, in preventing overactivation of the network, allow the most relevant parts like key symptoms in stroke prediction, to be emphasized more. Mathematically, this is modelled as the firing rate reduction of a neuron j when receiving input from an inhibitory neuron i in eqn5:

$$V_j(t) = V_j(t-1) + \sum_{i \in I} w_{ij} \cdot S_i[t] - \theta \quad (5)$$

Where: $V_j(t)$ is the membrane potential of neuron j at time t, w_{ij} is the weight of the synaptic connection from inhibitory neuron i to neuron j, $S_i(t)$ is the spike train of the inhibitory neuron i at time t, θ is the threshold for neuron j to fire.

3.5 CLOUD INTEGRATION

In short, Cloud Integration refers to tapping into the giants of cloud computing in order to scale up for storage and processing with an eye toward dealing with large healthcare datasets and developing complex models like SNN. The cloud infrastructure includes the much-awaited distributed model training, much of which used to happen over long computation time because it involves splitting the entire workload into different servers. It has, therefore, opened doors to enormous storage for vast amounts of medical data where they are also easily accessible and manageable. Cloud integration enables the uploading of predictive models; thereby, stroke risk prediction will be

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easy to do. In addition, it offers periodical updates and retraining of models, leading to continual accuracy as fresh data is acquired.

4. RESULT AND DISCUSSION

Figure 3 shows various performances relating metrics of the evaluation model metricized by accuracy, precision, recall, and F1 score, which are all graded on y-axes along with their specified percentage. In actual fact, the model's accuracy is 99.48%, which is somewhat higher than those of precision and F1 of 99.49% and 99.48%, respectively. Recall is the lowest among the four metrics, measuring 99.47%. The percentages in general are so high that the model correctly identifies even positive and negative cases. The entry provisioned through the parameters alone reflects the effective, sound, and versatile nature of the model for the intended application.

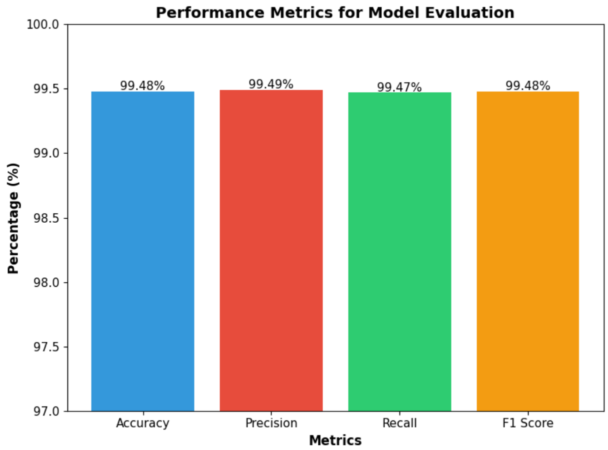

Figure 3: Performance metrics

The relationship between latency (in seconds) and data-rate (in Mbps) for three different cache sizes, that is 8',16', and 32', is depicted herein. Latencies decrease as data-rates increase across all cache sizes, as expected because an increase in the data-rate generally decreases the time it takes to transfer data. The plot shows three distinct lines for each of the cache sizes: red for cache-size 8, green for cache-size 16, and blue for cache-size 32. It is clear that a larger cache size incurs lower latency for any given data-rate, with the blue line (cache-size 32) being the lowest, followed by green (cache-size 16), with red (cache-size 8). This indicates that an increase in cache size increases system performance by decreasing latency for higher data-rates.

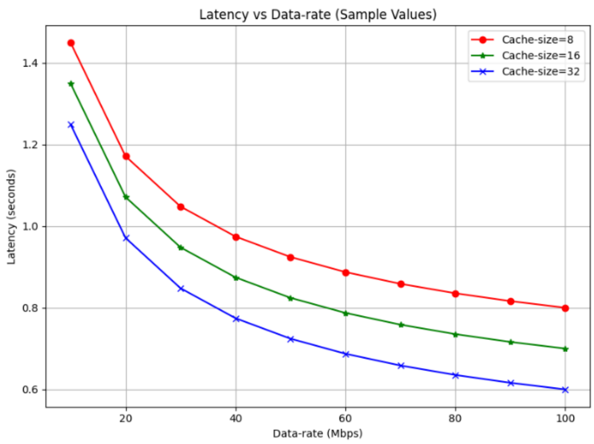

Figure 4: Latency vs data-rate

ROC curves are one of the most apt tools for the evaluation of the performance of binary classification models. The x-axis indicates the False Positive Rate (FPR); the y-axis indicates the True Positive Rate (TPR), which is also called sensitivity or recall. The blue curve exhibits the performance of the given model, an Area Under the Curve (AUC) value of 0.9948, which means the model is performing exceedingly well, with a value almost equal to 1. The distinction between the two classes considered, namely the positive and negative classes, is such that an

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AUC value very close to 1 is indicative of the goodness of the model in doing this distinction. A dashed diagonal line indicates the random classifier, whose AUC is 0.5, implying the model has no discriminative power. The way the ROC curve is situated far above this line gives credence to the model predicting way better than random guessing.

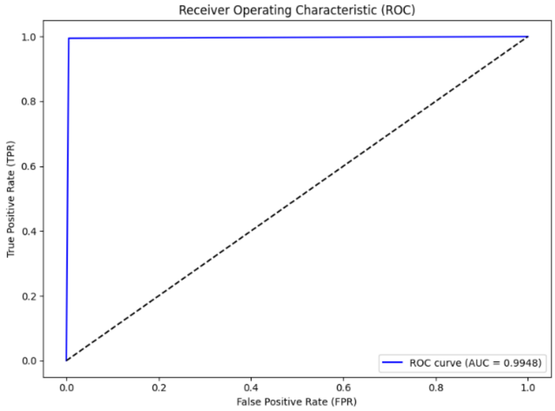

Figure 5: Receiver Operating Characteristic

CONCLUSION

In this paper, a new methodology is reported for applying Spiking Neural Networks with cloud computing for predicting outcomes after stroke. This combination has been validated as a new model which best fits into a robust, scalable, and accurate framework for stroke risk prediction. SNNs can capture the temporal dynamics of symptoms and risk factors related to strokes, while cloud integration will help manage and process bulky health datasets to ensure timely updates and continuous improvement of the model. The model will be able to more effectively understand and predict stroke risk through Symptom Severity Scoring, as well as Target Encoding. While the intervention targets stroke, it creates the flexibility of an adaptive system that can easily be implemented in any healthcare setting. It will become a model to offer better stroke prediction. The embedding of AI and cloud systems opens the doors for more trustworthy systems to prevent strokes which, in turn, will benefit healthcare professionals and patients through better decision-making and interventions.

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