Data Mining and Machine Learning In Medicine

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***Abstract*—some text**
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I. Introduction

Some text introducing the concepts - classifiers - image classifiers - convolutional NN - model refinement

In this report, a selection of differing machine learning (ML) techniques are explored. Each technique was chosen based on its area of application. The subject area of medicine was chosen for exploration, and a selection of datasets are explored with different features and formats: (i) a collection of brain magnetic resonance imaging (MRI) images that exhibit three cancer-based pathologies; (ii) a tabular dataset containing patient demographic and healthcare-related information related to stroke pathology; (iii) ?.

Stroke is a huge problem to global health; it remains one of the most common causes of death and disability [1]. The use of ML on stroke datasets is becoming a common practice because it makes it much easier for doctors to spot risks sooner and make better choices on the best treatment option for the patient [2]. The goal was to test different ML models to see which ones are best at classifying data and how unbalanced data impacts accurate predictions.

To approach the ML problems, an understanding of previous literature on the topic is required for an effective workflow. Academic papers were reviewed to gain an effective skill set and background knowledge required to begin experimentation.

II. Literature

ML as a concept is the basis of the field of artificial intelligence (AI); the primary purpose of ML is the generation of algorithms that are able to learn. In this regard, research has focused on the optimisation of these systems by generation of new techniques and identifying the most optimal combinations of pre-existing software/hardware [3].

ML is a popular tool in stroke research and its used to help spot problems earlier and assess patients more accurately. Large-scale research clearly shows that age, blood pressure, heart conditions, and blood pressure all play a role in how stroke affects a patient, hence the use of predictive modelling is needed to identify issues and intervene as early as possible [1]. Traditional statistics methods, like logistic regression are popular in healthcare because they're easy to interpret and identify factors that contribute to a patient's risk.

A. Logistic Regression

According to Aboong [4], logistic regression effectively points out the main stroke risk factors, proving it's a great tool for analysing organised medical datasets. Heo et.al [2] developed a machine learning model for predicting stroke outcomes, and their work showed how effective machine learning methods work better than the usual scoring tools. A big challenge, though is that stroke datasets usually suffer from a severe class imbalance and this can negatively affect a model's performance. Using techniques such as Synthetic Minority Over-sampling Technique (SMOTE) to balance the data has proven to improve the model's ability to find rare conditions in medical datasets [5]x.

The MRI image set relies on the classification ML technique; the specifics of this are introduced here.

B. Image Classifiers

This selection was reinforced by past research on brain cancer MRIs [6]. In particular, a convolutional neural network (CNN) was deployed. This ML technique has been shown to be highly effective in image classification [7]. A review into CNNs describes the typical architecture and construction techniques [8]. As the task differs, the design of the CNN can change, although the general format remains essentially the same. This typical structure, shown in Fig. 1, is comprised of ordered convolutional and pooling layers that come together to make a feature extractor. The inputted data is converted into a feature representation. In combination with this, fully-connected neural layers are integrated with activation functions to perform the desired ML operation.

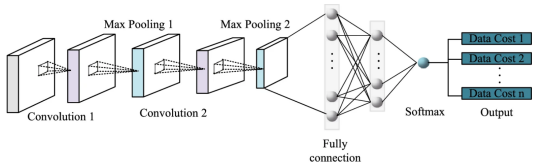


Fig. 1: Convolutional Neural Network Architecture [8]

Prior to data being used in ML, in order to increase suitability and feasibility of the model training, it should receive some sort of pre-processing. In order to effectively train a model, the data should be affected in a way that benefits the robustness and accuracy of the training process [9].

1) Pre-Processing: In image classification, effective pre-processing has been shown to increase the rate of identification [10]. For very large datasets, where manual review is not possible, automatic pre-processing is a must. Studies show that image cropping and reshaping, image resizing, and background noise removal are beneficial to the training process.

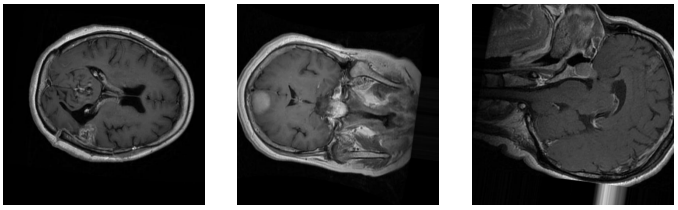
III. Data Analysis and Exploration

Based on the literature discussed previously, the data used in the following scenarios has undergone careful analysis in order to understand and prepare for upcoming ML.

The MRI classifying dataset was sourced from a comprehensive collection of MRI images collected from a series of hospitals in Bangladesh [11]. The data holds great value and significant effort was made to collect and label high quality images.

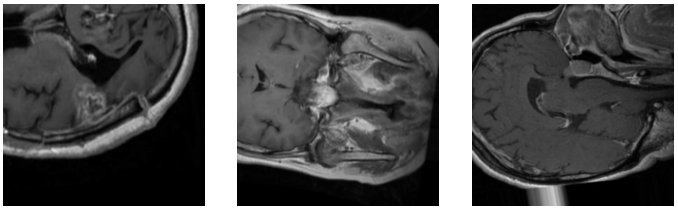
A. Brain Cancer MRI's

A sample of the three classes of data present is shown in fig. 2, pictures (a to b). The proprietor has already uniformly resized the images to an equal length and height. The ML for this set uses the hold-out method, 70% of the data is used for training, with the remaining 30% used equally between validaiton and training. To avoid bias or overfitting the data is shuffled using an scikit-learn cross-validation function that returns stratified randomised folds [12]. For the three sets some further ML specific pre-processing steps are executed, with training having more:



(a) Glioma (b) Meningioma (c) Tumor

Fig. 2: Sample images from MRI scans



(a) Glioma (b) Meningioma (c) Tumor

Fig. 3: Preprocessed sample images from MRI scans

- Random resized crop to 224×224 pixels
- Random horizontal flip with 50% probability
- Conversion to 3-channel greyscale
- Conversion to tensor format
- Normalisation to floating-point values in range [0,1]

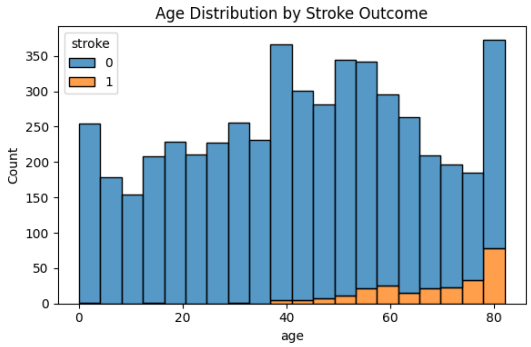


Fig. 4: Age Distribution by Stroke Outcome

- Standardisation using ImageNet mean and standard deviation

Additionally, the stroke dataset presented some inherent issues.

B. Stroke patient data

The stroke dataset used contains 5,110 patient records with demographic and clinical attributes such as age, heart disease, BMI, hypertension and average blood sugar level. The main variable (stroke) is binary. A small amount of missing BMI data was filled in by using the mean value.

A major challenge with this dataset is how unbalanced it is, with only about 3.4% of the cases actually having a stroke. The data exploration carried out indicated a higher chance of stroke among individuals within the age range of 50-80 years as shown in Fig. 4 and those with elevated glucose levels. When correlation analysis was carried out, it showed that age, hypertension and heart disease had subtle but meaningful relationship with stroke occurrences.

To get the data ready for training, word-based features were converted to 0/1 columns so the models could process them. All numerical values were also rescaled to a similar range to ensure no feature dominated the other while the model was trained. To deal with the class imbalance problem, SMOTE was used to generate synthetic stroke cases, which helped in detecting rare instances of stroke. The preprocessing and exploration guided the modelling choices in later stages.

After the initial data-processing step has been completed for all the datasets, the ML algorithms can now be established.

IV. Experimental Setup

As the content of the datasets varies in format and shape, the experimental setup for each varies too.

A. Baseline Training and Evaluation Experiments

For the stroke dataset, after the data was cleaned, three primary machine learning models were used.

B. Stroke analysis

The selected models were:

- K-Nearest Neighbours (KNN)
- Logistic Regression

- Random Forest Classifier

The data was split into two parts for training and testing, 70% was used for training the models and the remaining 30% was set aside to test how well they performed. The performance of the models were evaluated using four main measurements; accuracy, precision, recall, and F1-score. After applying SMOTE, the models were retrained.

C. Neural Networks

To ensure a balanced evaluation of the stroke data and to compare with the classical models, a multi-layer perceptron (MLP) was used to train the balanced data.

V. Results

Concerning the stroke prediction set. When the models were applied to the unbalanced data, the results showed high accuracy, but barely predicted any actual strokes (low recall).Which means they usually just guessed "no stroke" every time. Logistic Regression performed best overall as shown in Fig. 5 and table I, it has a strong recall score of 0.79 for the stroke cases while maintaining a good accuracy. This improvement shows how important it is to deal with unbalanced data when making predictions. The neural network achieved a high accuracy of 92% but struggled to identify actual stroke cases (low recall), which suggests it had difficulty in learning the patterns of the minority class.

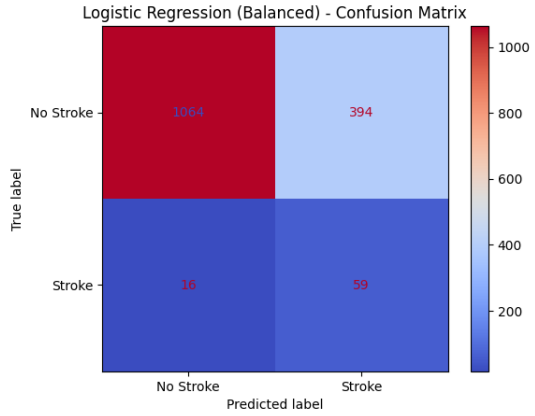


Fig. 5: Confusion matrix for logistic regression (SMOTE-balanced dataset)

TABLE I: Classification report for stroke prediction

Class	Precision	Recall	F1-Score	Support
No Stroke	0.99	0.73	0.84	1458
Stroke	0.13	0.79	0.22	75
Accuracy	0.73	–	–	1533
Macro Avg	0.56	0.76	0.53	1533
Weighted Avg	0.94	0.73	0.81	1533

References

[1] V. L. Feigin, B. A. Stark, C. O. Johnson, G. A. Roth, C. Bisignano, G. G. Abady, M. Abbasifard, M. Abbasi-Kangevari, F. Abd-Allah, V. Abedi, A. Abualhasan, N. M. Abu-Rmeileh, A. I. Abushouk, O. M. Adebayo, G. Agarwal, P. Agasthi, B. O. Ahinkorah, S. Ahmad, S. Ahmadi, and Y. Ahmed Salih, "Global, regional, and national burden of stroke and its risk factors, 1990–2019: a systematic analysis for the global burden of disease study 2019," *The Lancet Neurology*, vol. 20, no. 10, pp. 795–820, Sep 2021. [Online]. Available: https://www.thelancet.com/journals/laneur/article/PIIS1474-4422(21)00252-0/fulltext

[2] J. Heo, J. G. Yoon, H. Park, Y. D. Kim, H. S. Nam, and J. H. Heo, "Machine learning–based model for prediction of outcomes in acute stroke," *Stroke*, vol. 50, no. 5, pp. 1263–1265, May 2019. [Online]. Available: https://www.ahajournals.org/doi/10.1161/STROKEAHA.118.024293

[3] R. Abdulkadirov, P. Lyakhov, and N. Nagornov, "Survey of optimization algorithms in modern neural networks," *Mathematics*, vol. 11, no. 11, 2023. [Online]. Available: https://www.mdpi.com/2227-7390/11/11/2466

[4] M. Aboonq, "Potential role of logistic regression analysis to identify significant risk factors associated with stroke," *Bulletin of Egyptian Society for Physiological Sciences*, vol. 44, no. 1, pp. 17–28, Jan 2024.

[5] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "Smote: Synthetic minority over-sampling technique," *Journal of Artificial Intelligence Research*, vol. 16, no. 16, pp. 321–357, Jun 2002.

[6] J. Kang, Z. Ullah, and J. Gwak, "Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers," *Sensors*, vol. 21, no. 6, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/6/2222

[7] P. Wang, E. Fan, and P. Wang, "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning," *Pattern Recognition Letters*, vol. 141, pp. 61–67, jan 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167865520302981

[8] X. Zhao, L. Wang, Y. Zhang, X. Han, M. Deveci, and M. Parmar, "A review of convolutional neural networks in computer vision," *Artificial Intelligence Review*, vol. 57, no. 4, Mar 2024. [Online]. Available: https://link.springer.com/article/10.1007/s10462-024-10721-6

[9] M. Salvi, U. R. Acharya, F. Molinari, and K. M. Meiburger, "The impact of pre- and post-image processing techniques on deep learning frameworks: A comprehensive review for digital pathology image analysis," *Computers in Biology and Medicine*, vol. 128, p. 104129, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0010482520304601

[10] P. M. Diop, J. Takamoto, Y. Nakamura, and M. Nakamura, "A machine learning approach to classification of okra," in *2020 35th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC)*, 2020, pp. 254–257. [Online]. Available: https://ieeexplore-ieee-org.hwu-ezproxy.idm.oclc.org/document/9183312

[11] M. M. Rahman, "Brain cancer - mri dataset," *Mendeley Data*, vol. 1, Aug 2024. [Online]. Available: https://data.mendeley.com/datasets/mk56jw9rns/1

[12] scikit learn, "sklearn.model_selection.stratifiedshufflesplit." [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.StratifiedShuffleSplit.html