Brain Hemorrhage Detection

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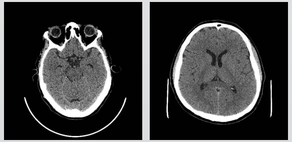
Abstract

The human brain, the most complex and crucial organ we have, serves as the command center for the entire body controlling how we move, respond, and think. Brain hemorrhages, otherwise known as a brain bleed, is a serious condition that could possibly be fatal if left untreated. It is estimated that there are approximately 40,000 to 67,000 brain hemorrhages every year in the United States. Mortality can range from 51% to 65%, with half of these deaths happening within the first two days. Because of this, accurately identifying a hemorrhage is pivotal for the life and well being of the patient.

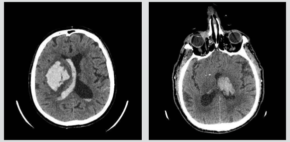
The purpose of this research focuses on the effectiveness of five different models, such as RNN, Attention RNN, CNN, SVM, and Logistic Regression, to identify whether or not a brain hemorrhage has occurred. The dataset contains a total of 6795 CT greyscale images of the brain where some include bleeding and others are completely normal. By comparing the accuracy scores, confusion matrix, and F1 scores, this research will provide critical accuracy in detecting brain hemorrhages to potentially improve early diagnosis and outcomes.

Background

Brain imaging plays a critical role in diagnosing neurological conditions and is essential in fields such as neurology and radiology. Brain scans, particularly CT and MRI images, are analyzed to detect various types of brain hemorrhages, each with its distinct characteristic and potential underlying causes. These types of hemorrhages are either diseases in themselves or key indicators of other serious neurological conditions.



Normal Brain CT Scans



Hemorrhagic Brain CT Scans

The dataset used in this project is comprised of Computed Tomography (CT) scans which are 3D representations of the body created using a combination of X-rays and computer processing to generate detailed cross-sectional images. These images are widely used in medicine because they offer fast and non-invasive visualization of organs, bones, and tissue with great accuracy. Because of this, they are the most common method used to detect brain hemorrhages and even show possible related injuries such as skull fractures or brain swelling.

Methods

Preprocessing: Resize all 6795 images from 512 x 512 to 128 x 128 grayscale. Randomly applied horizontal and vertical shifts, rotations, zooms, shears, and horizontal flips to prevent overfitting. The training set was 70% of the data while the validation was the remaining 30%.

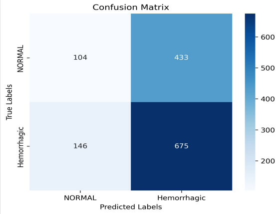
Logistic Regression: Each image was flattened into a 1D array to train the logistic regression model. Max iteration was 1000.

SVM: Each image was flattened to be able to train the SVM model. Standard scaler for standardization. Finally, the kernel used for this model is radial basis function (RBF).

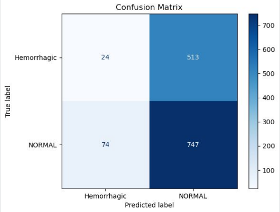
CNN: 5 Layers where each includes a 3x3 kernel convolution (# of filters: 32, 64, 128, 256, 512) with 0.01 L2 regularization, batch normalization, 2x2 max pooling, and a 30% dropout. After the 5th layer, global average pooling was applied into a dense layer with 256 neurons and was also batch normalized and 50% was dropped. Finally, it goes into a dense layer with 1 neuron returning the prediction using sigmoid.

RNN: This model reshapes images into sequences and use two simple RNN layers (64, 128 neurons) to capture sequential pattern, followed by dense layers for binary classification. Dropout layers (30%) to reduce overfitting, with sigmoid function to predict the probability of the positive class

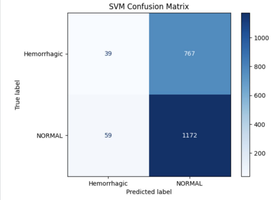
Attention-RNN: The model's input is a grayscale 228×228 image with augmentation. It incorporates a dropout layer after every learning layer: the dropout rate is 0.5 for the LSTM layers and 0.3 for the dense layers. The distinguishing component of this model is its attention mechanism. Additionally, a learning rate scheduler with a factor of 0.5 and patience of 3 was employed.



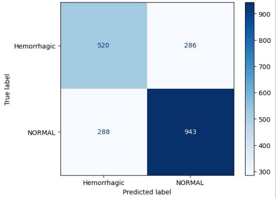
Recurrent Neural Network (RNN)



Attention-based RNN



Support Vector Machines (SVM)



Convolutional Neural Network (CNN)

Results

Model	Validation Accuracy	Time for Training	Brief Description
Logistic Regression	0.521	~3 min	Benchmark model for the dataset. Poor accuracy for the binary classification at only 52%.
SVM	0.595	~30 min	The better accuracy using traditional machine learning algorithms at 59%. Radial Basis Function (RBF) kernel had the highest accuracy.
CNN	0.731	50 Epochs: ~35 min	Used 5 layers using dropout and L2 regularization to prevent overfitting. Model still suffered from overfitting.
RNN	0.574	50 Epochs: ~13 min	Use 5 layers with reshape images, 2 RNN layers, dense layers and output layers.
Attention-RNN	0.605	50 Epochs: ~30 min	The architecture consist of 2 LSTM layers, an attention layer, and two dense layer. In addition, i added dropout layers.

Conclusion

Despite incorporating randomization through preprocessing and other techniques, our models still exhibited overfitting to the training data, which negatively impacted their accuracy on unseen data, as reflected in the validation set. Among all the models tested, the CNN performed the best, as anticipated, given its ability to capture complex patterns in images. Surprisingly, traditional machine learning methods performed better than expected, despite their inability to learn in the same way as neural networks.

Future Direction

For the future direction of this project, access to better hardware for faster processing would enhance the computational efficiency and optimize performance. Additionally, expanding the dataset to include a larger and more diverse set of patient data will improve model training and validation. Finally, experimenting with different machine learning algorithms to explore potentially improved accuracies that align with the model's optimal parameters.

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