CAPSTONE 3 FINAL REPORT

In the quest to identify and address emergency situations and various crises in the most effective way possible, resources and methods that are adapted to the modern forms of communication are called for. Social media platforms and giants such as Twitter are highly popular for being able to quickly engage with other users in a multitude of topics including current events for providing the means to send short bursts of texts packed with the necessary details to relay to others globally. For news broadcasters and emergency relief effort workers alike, Twitter has become a burgeoning and cemented resource in efficiently detecting emergencies and crises in need of public service announcements and disaster relief services which is a matter of life and death. This quest in searching for a medium that is updated constantly in real-time with the latest current events including disasters has led us to Twitter being a potential top resource as Twitter can be accessed at anytime, anywhere with the ubiquity of smartphones with users being able to feed the platform with the latest happenings and news quickly relayed in short and concise texts.

In the heart of the digital age, and in the current iteration of the internet that was motivated by the need to expand and develop social media, what is the first place the average citizen reports current events outside of family or friends? What other social media platform just so happens to be perfectly formatted for users to send short texts packed with important details that is consistently updated in real-time? Where the namesake and the text format are the unique identifiers of the platform? Of course, the answer is no other than Twitter.

Making use of Twitter to promptly raise awareness and locate disasters to respond to immediately is of utmost importance to communities worldwide. A seemingly mundane tweet added to the twitter feed that at first glance appears to be a world away (albeit paradoxically as social media platforms like Twitter interconnect distant places into a 'global village' of sorts), can suddenly transform to be of a critical and dire situation in which any one of us is compelled to take immediate action at the stake of our community, property, livelihoods, or our very lives. Having a smartphone with access to Twitter whereby we may interact with at any moment, allows us to relay information where we can help others to get the relief they need, broadcast critical news updates to the agencies and organizations at the local level to serve the affected community, and reach out for help ourselves as quickly as possible and maximize our resources and chances of receiving relief efforts through multiple mediums. One major issue however that needs to be raised and addressed is distinguishing and separating between tweets that contain highly similar words and phrasing but may or may not necessarily be signaling an emergency. While a human user can easily distinguish by virtue of context within the text, getting an algorithm to do the same with such accuracy proves to be the challenge here. Since we need an algorithm that can match the ability of the human brain to distinguish between levels of critical demand, in our case here a binary classification problem of emergency and non-emergency, deep learning models were used to meet this challenge as it mimics the behavior of the human brain albeit to an imperfect degree; however, we have attempted to close this gap as much as possible.

While finding the solution to meet this demand, three different types of neural networks were tried including simple, convolutional, and recurrent neural networks. Before proceeding to use any of these models, the dataset of tweets needs to be converted to a data frame, divided up into a label and text set, and then cleaned and preprocessed, presenting the text to be inputted into the model free of punctuations, numbers, spaces, etc. Furthermore, the new distinct label and text features would need to be further separated into train and test sets for the model to get adequate training on similar data and be able to predict future datasets as accurately as possible. Finally, we created class objects of each of the three models starting with the simple neural network model which is created with three layers which are made up each of a collection of neurons meant to imitate the functioning of the human brain; these layers include an embedding, flatten, and dense layer. Following this the model was trained using the train set and then evaluated using the test set for use as the prediction set. Overall, the simple neural network was found to have minimal overfitting with accuracy of the training set reaching around 82%, the validation set of the train set reaching around 76%, but the prediction accuracy achieving about 80%. The second neural network attempted was the convolutional neural network, usually used for 2D data classification such as images but is reputed to work just as well with text data. After instantiating a class object for the convolutional neural network model, four layers were added to this model including the embedding, conv1D or convolutional one dimension, the global max pooling 1D, and the dense layer. After fitting the training data and evaluating the model on the prediction set, the accuracy for the train set was 90% and validation accuracy at 80% with the overfitting having a bigger discrepancy than the previous model, and the accuracy of the prediction set achieving 82%. The third model attempted, the recurrent neural network which is a neural network optimized in working with sequence data which text is a sequence of words, was instantiated with three layers including the embedding, long-short term memory or LSTM, and the dense layer. After training the model on the training set and evaluating the model's performance on the prediction set, the accuracy for the train set achieved 57% with its validation set at 56% showing very little overfitting, and the accuracy for the prediction set achieving 57% accuracy. Even though the recurrent neural network model resulted in the least overfitting, I ultimately did not opt for this model as the accuracy was way too low and in terms of detecting tweets that can mean life and death, this was not nearly sufficient in prediction accuracy. Likewise with the simple neural network, I did not opt for this model neither as the prediction accuracy was paramount for the objective here even though the prediction results were more respectable. I chose the convolutional neural network model as this model achieved the highest prediction accuracy, where its value did improve over the validation accuracy of the train set. I overlooked the overfitting here solely due to the model being deployed exclusively for datasets consisting of tweets so any future unforeseen datasets would be extremely similar in features and values. Also, this model would be employed for data where predictive accuracy is critical so the higher the accuracy on unforeseen data, the better as lives depend on it.

With building and eventually deploying an algorithm such as our convolutional neural network, a short list of to-dos from anyone reading (or perhaps listening) to put into action would contribute profoundly to the advancement of accelerating disaster relief outreach to those in need and further improving upon the models needed to aid us in our quest of detecting these emergencies as accurately as possible. When out and about in any location and you stumble upon a real-time disaster, simply draw out your smartphone, launch Twitter, and tweet and/or document the incident. In doing so, we will assist the model in improving upon its prediction accuracy and make further progress, facilitate the dissemination of critical info by supplying news agencies the news they need to inform the public, be a supportive ally for emergency relief organizations to speed up their response time, and most of all rescue lives.