We have been losing the battle against suicide. Over the past two decades suicides have risen by 5%, increasing at a rate disproportionate to other leading causes of death. Efficacious suicide prevention and intervention is necessary. There is an exigent ethical demand for applications of new technology that growing problem. Understanding the psychological conditions surrounding a suicide can present a challenge. Suicide notes provide insight into the mind of the deceased and can be utilized to recognize motives and sentiments behind the suicide. Utilizing artificial neural networks and cognitive network science to analyze the emotional and semantic content of suicide notes could foster understanding at an unprecedented level. The data generated by these algorithms could significantly improve prevention efforts by identifying patterns within suicidal behaviour and integrating psychological theories to create valuable interventions.

Research Questions
1. Can select artificial neural networks detect and classify emotional content at the sentence level?
2. Can select cognitive networks identify a particular semantic and emotional structure within suicide notes?

Methodology
A literature review was conducted to understand the current application and efficacy of particular cognitive and artificial neural networks analyzing suicide notes. Scholarly journal articles, reports, and datasets were found by using electronic databases (IEEE Xplore, JSTOR, ProQuest, PubMed, ScienceDirect, and Springer Nature Journals). The specific search terms involved "neural network suicide notes", "deep learning semantic content analysis", "natural language processing semantic parsing", "cognitive networks suicide notes", "emotional valence detection suicide notes", and "supervised vs unsupervised deep learning suicide". Given the scope and variety of neural network applications and potential processing/classifying goals, limitations were put in place. The extant literature was screened for inclusion based on the following criteria:

- Corpus of genuine suicide notes were used.
- Emotional and semantic content was classified and analyzed.
- Artificial neural networks were limited to either convolutional or recurrent neural networks.
- Notes were incorporated in the research, scholarly journal articles, reports, and datasets based on their meeting of the inclusion criteria, relevance to the topic, and had to be written in the English language.

Based on the inclusion criteria established, 7 published journal articles were selected and analyzed. The sources ranged from 2020 to 2022, enabling current look at the present condition of cognitive and artificial network analysis of suicide notes. A total corpus of 344 authentic suicide notes were used in classifying emotional/semantic content and demonstrating emotional/semantic structures.

Data Collection
Three trained annotators reviewed all available suicide notes and conducted sentence-wise emotional labeling with each sentence representing at most one emotion from a 15-emotion tagset. (abuse, anger, blame, fear, forgiveness, guilt, happiness, peacefulness, hopefulness, hopelessness, love, pride, sorrow, and thankfulness, information, and instructions). Cohen’s Kappa coefficient was used to analyze inter-annnotator agreement. Defined as:

\[ K = \frac{P_o - P_e}{1 - P_e} \]

Final annotations for the data set were made following majority voting on the individual annotations. The annotated dataset was split into train and tests sets at an 80:20 ratio. The three artificial neural networks, convolutional neural network, long short-term memory, and gated recurrent unit were then tested individually and collectively via majority voting (MV). The annotated dataset was split into training, validation, and test sets using a stratified procedure. The co-occurrence of words and the sentence context were used to determine the emotional content of the sentence. The co-occurrence of words and the sentence context were used to determine the emotional content of the sentence.

Cognitive Networks
Suicide notes were analyzed using two cognitive linguistic networks. Co-occurrence and subject-verb-object (SVO) networks were used to identify potential structural relationships within suicide note content. Positive/negative/neutral labels were then used in a signed structural balance analysis (Fig.14). A signed network with positive and negative links was obtained, and degrees of balance were found by calculating the fraction of balanced node triplets. The resulting adjacency matrix was used to train a cognitive network, representative of a large population without suicidal tendencies. (Fig.2)

Artificial Neural Networks
1. Convolutional Neural Network (CNN)
   Used extensively for classification tasks. CNN can be trained with word vectors, acting as feature extractors that encode semantic features of words. CNN utilizes layers with convolution filters that are applied to local features and merges the output of the layers. The convolutional output goes through a max pooling operation before it is passed through a fully connected layer. This creates a representation (document vector) of the emotionally salient words in a suicide note. (Fig.4)

2. Long Short Term Memory (LSTM)
   Used extensively in natural language processing and sentiment classification as an LSTM cell remembers values over arbitrary time intervals, selectively reading and forgetting information using three gates. LSTM thus overcomes the vanishing gradient problem and is uniquely suited learning long-range dependencies in text. This has immediate applications for suicide notes which require the ability to analyze the content contextually not word by word. (Fig.5)

3. Gated Recurrent Unit (GRU)
   Faster to train than LSTM containing only two gates (update and reset) while maintaining the ability to handle long term data and efficiently learning long-range dependencies. GRU offers similar natural processing results to that of LSTM while exhibiting superior performance on smaller data sets due to its speed in sentiment classification. (Fig.5)

Conclusion
We now have the tools to evolve our current understanding of suicide and begin developing more efficacious explanatory modalities, and plans for intervention. The accuracy of algorithmic networks emotional classification and recreations of internal semantic structures are far from perfect, but they do show promise. New applications of these cognitive and artificial neural networks are already demonstrating their ability to reconstruct knowledge matrices and emotional states of those who have died by suicide. Revealing the nuanced relationships and patterns within the content of suicide notes may be the first step in understanding what better suicide prevention and care looks like.

Future Considerations
Revealing the nuanced relationships and patterns within the content of suicide notes is significant information that can lead to a better understanding of pragmation of our currently debated theories, models, and frameworks for suicide ideation (Interpersonal Theory of Suicide, Integrated Motivational-Volitional Model, Developmental Model of Suicide). These frameworks are based on semiotic, Cultural Theory and Model of Suicide). Additionally, we should not rush into mass data scraping from social media to inform these networks via contextualized suicide ideation, as that raises ethical concerns surrounding privacy and requires additional vetting for accurate data collection.