SUICIDAL IDEATION PREDICTION USING CONVOLUTIONAL NEURAL NETWORK BIDIRECTIONAL LONG SHORT-TERM MEMORY (CNN-BILSTM)

Christianah T. Oyewale[1], Joseph D. Akinyemi[2], Ayodeji O.J Ibitoye[3], Olufade F.W Onifade[4]

School of Collective Intelligence, Mohammed VI Polytechnic University, Morocco. oyewalechristianahtitilope@gmail.com[1],
University of York, YO10 5GH, United Kingdom[2],
University of Greenwich, United Kingdom[3],
University of Ibadan, Nigeria[4]

INTRODUCTION

Suicide is a mental health issue mainly cause by individual (eg mental illness, truma), social (eg stigma, use of media) or situational (bullying, drugs/alcohol) factors (Saxena et al., 2014). The ICIR research shows the rate of suicide in six countries showing the importance of early suicide detection (Fig 1).

Detecting suicide ideation in victim is primarily the task of the mental health practitioners. Due to access to internet by diverse people in ideating their minds which create vast amount of dataset on social media, Machine Learning researchers joined the mental health professionals to combat suicide.

Ability to predict suicide ideation can be crucial in preventing tragic outcomes. The aim of this research is to develop an enhanced suicide ideation prediction model by exploring and optimizing combinations of word embeddings (Word2Vec, FastText, and GloVe), classifiers (CNN-BiLSTM) and datasets (Aldhyani et al., 2022; Ghosh et al., 2022).

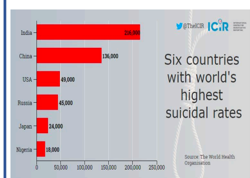

Fig. 1: Suicide Rate (Rebecca Akinremi, 2019)

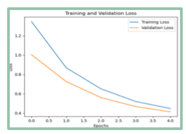

Fig. 2: CNN-BiLSTM Word2Vec Loss Curve

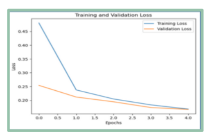

Fig. 3: CNN-BiLSTM FastText Loss Curve

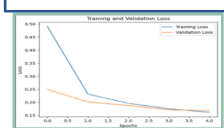

Fig. 4: CNN-BiLSTM GloVe Loss Curve

METHODOLOGY

Two datasets were used in this study, the publicly available Reddit dataset (Aldhyani et al., 2022) which comprises of balance classes (suicidal or non-suicidal) and Suicide Note (Ghosh et al., 2022), which comprises of imbalanced dataset.

The first dataset which was mainly used for model building, the suicidal text comprises of more negative words and has uniform distribution. While the non-suicidal text comprises of neutral and positive words, and rightly skewed. The second dataset was used in carrying out cross-dataset testing.

The both datasets were preprocessed by carrying out lowercasing, remove special characters and stop words, tokenization, sequence padding and text encoding.

The first experiment, Word2Vec, FastText and GloVe embeddings were used, three models were built. The CNN-BiLSTM architecture used can be viewed in fig. 5 and the implemented model in fig. 6. The model was trained with 64 batch size and 5 epoch.

The second experiment, the best model from the first experiment was further tested with the second dataset.

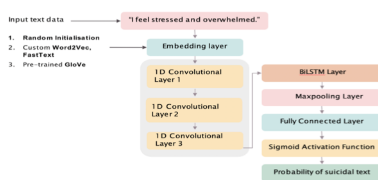

Fig. 5: CNN-BiLSTM Architecture

RESULT ANALYSIS & DISCUSSION

The accuracy, precision, recall and F1 Score of CNN-BiLSTM model built with Word2Vec word embedding had 94%, 90%, 90% and 90%, respectively. The model built with FastText had 94% for the four evaluation metrics. And the model built with GloVe had 93% accuracy and 94% for the remaining metrics. The loss curve for each of these model can be viewed from Fig. 2, 3 and 4, showing convergence and no overfitting.

Using F1 score, the model built with FastText and Glove, both had 94% but FastText outperformed GloVe in the other evaluation metrics. The model with FastText was used to proceed to the second experiment. As predicted, the model couldn't perform well on the second dataset which is the suicide note.

Comparing our study with earlier model where this study is extended from (Aldhyani et al., 2022), achieved an F1 score of 95%, overfitting was noticed. But from their second experiment, they achieved 84% F1 score after combatting the overfitting. Our three models which do not overfit outperformed theirs.

SAMPLE LITERATURE REVIEW

S/N	Author & Year	Problem	Method	Result/Contributions	Limitation / Future Work
1.	**Kang et al. (2021)**	Assess the prevalence and its clinical correlate of suicidal ideation among adolescent patients with depression	**Dataset**: 1637 (748 males & 887 females) **Approach**: Clinical data and self survey. **Classifier**: Interview	**Suicidal:** 625 **Not Suicidal** : 1,012	Time consuming Globalization Problem
2.	**Pan et al.(2021)**	Associations between adolescent suicide and psychiatric distress/ psychiatric morbidity	**Dataset:** 727 **Approach:** Phone Interview **Classifier:** Regression Analysis	**Lifetime suicidal ideation** – 11.4% **One-week suicidal ideation** – 2.8%	Telephone interview Structured questionnaire
3.	**Davidson et al.(2021)**	Provide context to job-related problems experienced before nurse death by suicide	**Dataset:** 203 **Approaches:** NLP & thematic Analysis **Classifier:** LSTM, CNN	Very little were positive	Small dataset. Exact result was not stated
4.	**Keshu et al. (2021)**	Detecting depression in social media users	**Dataset:** 5000 posts **Words Embeddings:** Word2Vec & TF-IDF **Classifiers:** NB, LR, RF, XGBoost, SVM & Transformer Model	**SVM:** 92% accuracy & F1 scores. **Transformer:** 98% accuracy & F1 scores	Data splitting (90 train 10 test) No cross dataset test
5.	**Soumitra et al. (2022)**	Suicidal or Not Suicidal. Causes of Suicide	**Dataset: 5699** **Words Embeddings:** Transformer **Classifiers:** RoBERTa, XLM-R, SpanBERT, and mBERT	**SpanBERT,RoBERTa, XLM-R :** 76% **mBERT:** 73%	Manual annotation No cross dataset test
6.	**ARKAITZ & AIQI (2022)**	Early detection of suicidal ideation	**Dataset : 232,074** posts (116,037 suicidal & 116,037 non-suicidal) **Word-Embedding:**TF-IDF & Word2Vec **Classifiers:** CNN–BiLSTM & XGBoost models	**CNN– BiLSTM:** 95% accuracy & F1 score. **XGBoost:** 87% accuracy & F1 score	No cross dataset test Can't generalized to other social medial platforms

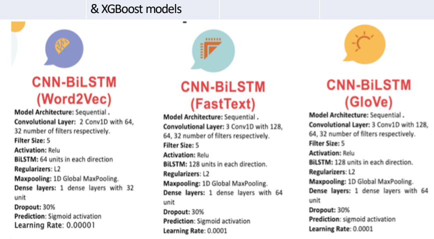

Fig. 6: Model Implementation

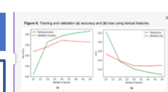

Fig. 7: Earlier Model Exp.1

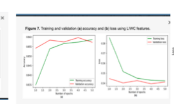

Fig. 8: Earlier Model Exp.2

Fig. 9: CNN BiLSTM FastText Exp.2

CONCLUSION

Suicide is a problem in public health. This research explored three word embeddings on two datasets with CNN-BiLSTM model and averagely achieved 94% F1 score. Further exploration by testing on a different dataset, the model didn't perform well.

This require further investigation to know the factors affecting the model from generalizing to a complete different dataset. Also, to enhance the performance, other word embeddings like transformers will be used in the future.

SAMPLED REFERENCES

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