IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Psychological Behaviour Classification based on Social Media Reviews Using Support Vector Machines

[1]Manoj R, [2]Dr. Pradeep N, [3]Dr. Sreenivasa B R

[1]M-Tech Student, [2]Professor and HOD, [3]Professor and PG Coordinator

[1]Department of Artificial Intelligence and Data Science,

[1]Bapuji Institute of Engineering and Technology, Davanagere, India

Abstract: Now a days mental health disorders are a major problem. Anxiety, depression, bipolar illness, long-term stress, and various personality disorders are common conditions. Due to non-availability and less access to physicians and other medical specialists, many issues go undetected. This method automatically determines whether a person is suffering from mental health issue is proposed in this research. To examine what people write and attempt to comprehend their behaviour, we employ a technique known as Support Vector Machines. The technique known as Term Frequency-Inverse Document Frequency to quantify what people write. I also employ a list of words that are related to emotions to obtain a better grasp of what individuals are writing. I used a corpus of texts from people to test our system. 52,680 writings were present. I am able to identify the type of behaviour they represented because they were all labelled and attempted numerous approaches of training our system to acquire the best results. The suggested approach performed well in classification across all behaviour categories. Compared to the systems used in this purpose, this is superior. Addition to that this tool that can be used to assess individuals' mental health issues instantly. Support Vector Machines is one tool for this and the outcome is satisfactory. The persons who are suffering from mental health issues will be benefitted from this system.

Keywords: Psychological Behaviour Classification, Support Vector Machine, TF-IDF, NRC Emotion Lexicon, Hybrid Feature Fusion, Mental Health NLP, Multi-Class Classification, Affective Computing.

I. Introduction

Mental health is globally significant issue now a days and many of the people are not receiving the very basic assistance and support. According to the report proposed by World Health Organization, over one billion individuals across the worldwide suffer from some form of mental health issue, yet only a small percentage receive the proper diagnosis and care [13]. There are many misconceptions and stigmas surrounding with health, and there aren't enough physicians and therapists available, particularly in countries like India. These days, a lot of people discuss their emotions in internet forums and the media [3], [4]. This allows us to use computers to determine whether a person is experiencing health issues. By examining the language they employ, we can achieve this. How they feel. The issue is that computers are not perfectly good at deciphering people's emotions from the language they use. They are able to count the number of times a word is used, but they are unable to truly understand its meaning. However, if we only consider people's emotions, we may overlook some crucial information. This essay attempts to address this issue by fusing two perspectives on words [1], [11]. To examine the terms peoples use, we employ a technique known as TF-IDF [15]. We also examine their emotions using a tool called the NRC Emotion Lexicon [2]. Combining both the methods leads us to train a model that will identify mental health issues in individuals by classifying their writing into seven categories: Anxiety, Bipolar Disorder, Depression, Normal, Personality Disorder, Stress, and Suicidal Ideation.

In this paper, we are accomplishing the following new things:
1. The NRC Emotion Lexicon and TF-IDF are being used to provide a method of examining words that can assist us in determining whether a person is experiencing mental health issues.
2. To determine whether our approach to word analysis is truly superior to simply employing TF-IDF, we are testing it.
3. To determine which computer software is most effective in determining whether a person is experiencing mental health issues, we are comparing it to other programs.
4. We are developing a website where anyone can go for assistance and determine their likelihood of experiencing health issues.

II. LITERATURE SURVEY

Studying people's behaviour and mental health is crucial since many individuals struggle with issues, and we have a wealth of information on behaviour from online settings, surveys, and also the social media devices we wear. Researchers have developed methods to increase the accuracy and dependability of psychological behaviour prediction systems by utilizing the machine learning, deep learning, and natural language processing techniques [3], [4], [5].

In 2026, Mamatha and colleagues suggested utilizing self-explanatory machine learning to determine a person's type of disorder based on behavioural and psychological data. Enormous machine learning techniques, integrating with Logistic Regression, Decision Trees, Random Forest, Support Vector Machine Techniques, Gradient Boosting, XGBoost, and AdaBoost, were tested. And obtained accuracy percentage of 83.33%, the AdaBoost approach was the most accurate. To increase the model's transparency, they additionally employed methods including SHAP, Partial Dependency Plot, and Individual Conditional Expectation. Nevertheless, this approach had many drawbacks; it was limited to data and required more processing resources to explain how it operated.

In 2025 Habiba Rashid Lamiya and team developed a system to predict personality using the Myers-Briggs Type Indicator (MBTI) and Natural Language Processing. They collected real-time text data through keylogging. Compared their systems performance to traditional personality assessments that use questionnaires. The system used Transformer-based language models to improve accuracy and scalability. It did a job analysing language but mainly focused on predicting personality and not on classifying mental health disorders.

In 2025 Swagata Panchadhyayee and his colleagues presented a framework for examining human behaviour. It integrated questionnaire results, audio sentiment analysis, and face expression analysis. To categorize states, they employed a different types of methods, along with Random Forest, OpenCV, dlib, and Natural Language Processing. Their framework outperformed classifiers with an accuracy of 85.4%. However, in order to function in real-time, it required additional processing power and data from sources.

In 2025 Dr. Arun Singh Chouhan and his group presented a model of machine learning to Students' device addiction was predicted using this methodology. To obtain the information they required, they employed a questionnaire. More than 3,450 students' replies are well utilized to train the Random Forest classifier. With a 91.40 percent accuracy rate, it was highly accurate. The F1-score, recall, and precision were all above 90%. When classifying pupils into moderate and high-risk groups, the model performed well. Only the data from the questionnaire was used. It made no use of social media or physiological data.

The year in 2024 Alexandru Robert Vlasiu and his team did a study. They examined the potential applications of Reality behavioural data. They sought to determine whether it might be used to the categorization of disability. Among these impairments were Attention Deficit Hyperactivity Disorder and Autism Spectrum Disorder. They examined gaze patterns, movement patterns, and user interactions with the VR device. To examine the data, they utilized Support Vector Machines, Random Forests, and Decision Tree methods. With respect to the early study, early diagnosis can be aided by reality behavioural analysis. With just 72 individuals, the dataset was small. This restricted the model's potential for widespread application. Examples of how technology may benefit humans include virtual reality models and machine learning models, like that one developed by Dr. Arun Singh Chouhan and his colleagues. The machine learning model and the Virtual Reality model are both tools.

In 2023 Abhinav P. V. Sa and team proposed a machine learning model used to predict behaviour in adolescents. This uses the WHO Global School-based Student Health Survey dataset. Several algorithms were tested, including Naive Bayes, Support Vector Machines, Decision Trees, Random Forest and XGBoost. The Naive Bayes classifier got the F1-score of 0.87. Regression models showed prediction performance. How ever the model relied heavily on questionnaire-based information. Did not monitor behaviour in real-time.

In 2021 Igor Kotenko and team presented a model that is used to predict mental states using the data from social network. They combined Latent Dirichlet Allocation (LDA) with the fast Text classifier. The team analysed Reddit posts to identify emotions and classify users mental states [10]. The approach worked well achieving an F1-score of 96% for detecting mental states. Its performance depended on the quality of social media text and that not work well along different online platforms.

III. RESEARCH GAP

There are some gaps in the research that has not been done so far. Here are a few things that still need to be concentrated more:

- The most available systems that try to detect people's emotions and behaviours depend only on one type of data and lack a systematic language to express its emotions. While solving problems with multiple options using very limited data types, the outcome may be uncertain and not predictable.
- Most of the models are using very significant computing power to learn and take decisions to perform well but it tends to be very slow and it’s very hard to understand its result. The models that perform well on test data and predict very good decisions more efficiently by consuming very less computing power.
- Health data often shows an imbalance, with abundant information on healthy individuals but limited data on those with certain personality disorders. This imbalance complicates decision-making.
- We often want to know the confidence level of our decisions. However, in mental health data, there is rarely discussion about how certain people are about their decisions.
- To verify if parts of our systems truly help us make wise decisions, we must conduct thorough studies.

The approach we are proposing seeks to fill in all of these gaps. It uses a combination of types of information and specific computer systems to make effective decisions. Additionally, it attempts to ensure that it is equitable, balanced, and timely. We test it frequently to ensure that it is functioning properly and to identify the components of the system that are truly assisting us in making wise choices. The research gap is something that the proposed system tries to address by using a Hybrid Feature Fusion SVM system with calibrated probability outputs, class-weight balancing 5-fold cross-validation ablation validation and a real-time deployment interface to solve the research gap. The research gap is a problem that the proposed system tries to solve.

IV. MATERIALS AND METHODS

The proposed system follows a step-by-step process:

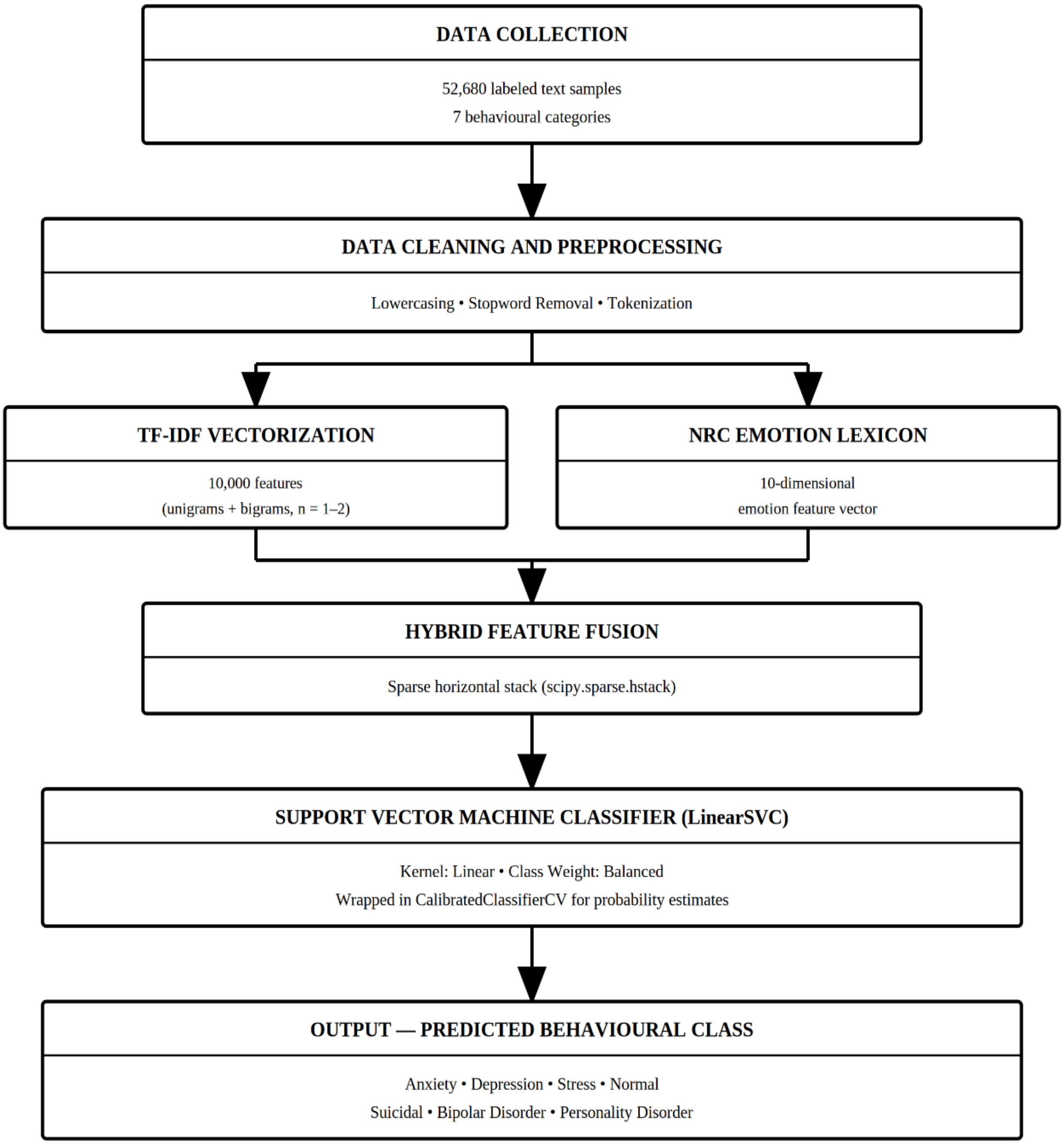

Figure 1: Proposed Hybrid Feature Fusion Pipeline for Psychological Behaviour Classification

1.Dataset

It has 52,680 text samples from media and clinical texts. These samples are. Belong to seven psychological behaviour classes. We split the data into 80% for training (42,144 samples) and 20% for testing (10,536 samples). Figure 2 shows how the classes are distributed. The classes are somewhat imbalanced with Depression (around 15,405 samples) and Normal (around 16,345 samples) having the samples and Personality Disorder (around 1,075 samples) having the least.

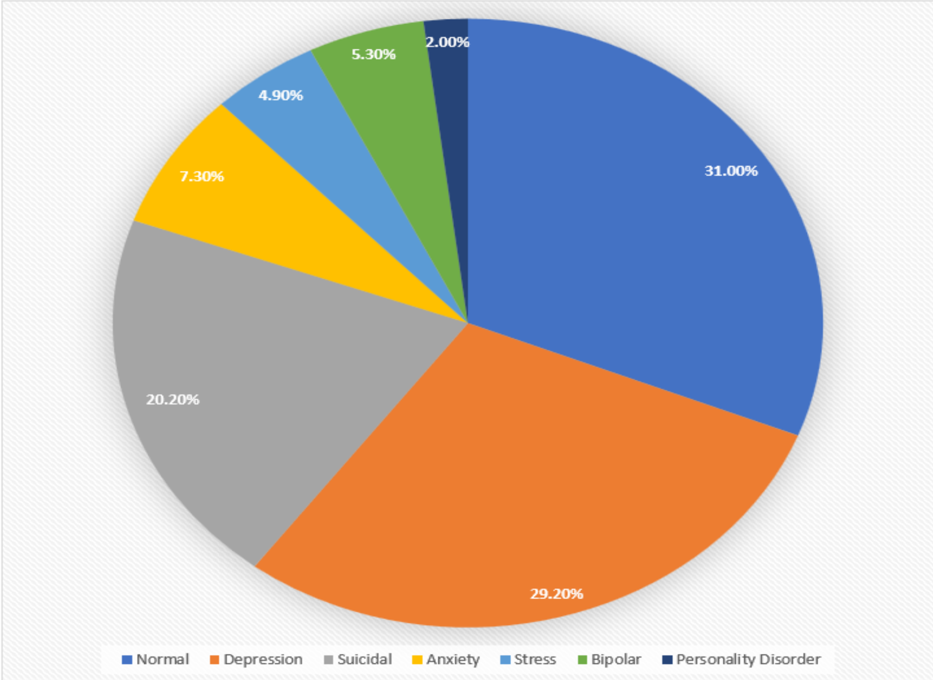

Figure 2: Class Distribution in the Dataset (N = 52,680)

2.Text Preprocessing

It cleans the raw text data using a process in the clean_text() module:

- We convert all characters to lowercase.
- We remove hyperlinks.
- We remove punctuation.
- We remove words like "the" and "and".
- We remove spaces.

3.Dual-Path Feature Extraction

It extracts two types of features from the cleaned text:

1.TF-IDF Features:

TF-IDF helps us understand how important a word is in a document [15]. We use a Tf idf Vectorizer to get these features. It looks at both words and pairs of words. The result is a sparse matrix.

2.NRC Emotion Lexicon Features:

The NRC Word-Emotion Association Lexicon tells us how words relate to emotions [2]. For each text sample we calculate what many numbers of words fit into each emotion category. This gives us a 10-feature vector. We adjust these features so they work well with the TF-IDF features.

4.Hybrid Feature Fusion

It combines the TF-IDF and NRC features into one. This keeps the structure of TF-IDF and along with that the emotion features will also be added.

5.Model Training and Hyperparameter Tuning

It uses a classifier because it works well with large sparse features [14]. We calibrate the classifier to get probability outputs. We handle class imbalance by balancing the class weights. We use GridSearchCV to find the parameters. We test values and choose the best one. The best value is 1. It takes 639.11 minutes to train the model.

6.Evaluation Metrics

I evaluated the model using Accuracy, Weighted Precision, Weighted Recall and Weighted F1-Score, performed on the set of test data. Also report averaged metrics to see how well the model does for each class.

V. RESULTS AND DISCUSSION

Cross-Validation Results

The stratified five-fold cross-validation in Table 1 shows the accuracy of each folds on training dataset gives the fold accuracies as displayed in Figure 3. The accuracy of 75.63% and standard deviation of just 0.49% indicates stability of the model and no overfitting due to high variance.

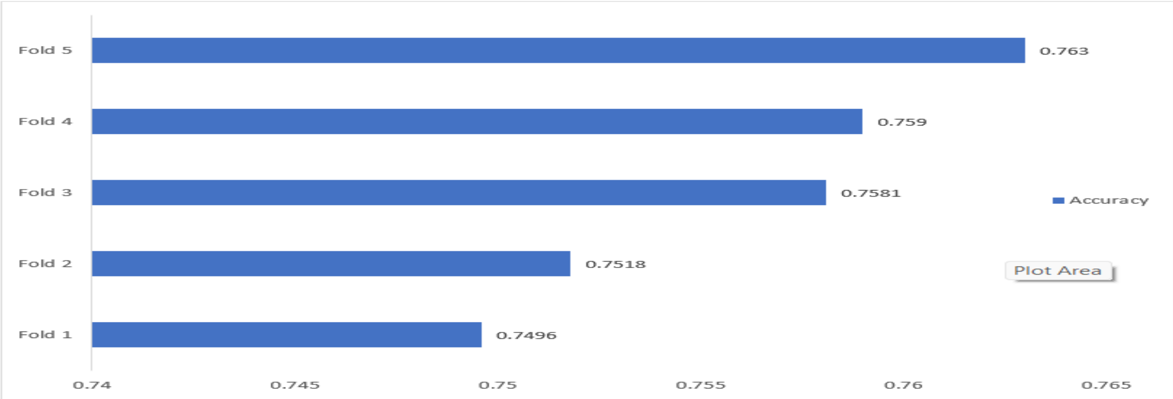

Figure 3: 5-Fold Cross Validation Accuracy per Fold (Mean = 0.7563, Std = 0.0049)

Table 1: 5-Fold Cross Validation Fold Accuracies

Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
0.7496	0.7518	0.7581	0.7590	0.7630

Comparative Performance of Models

Table 2 shows the comparative performance of all of the classifiers on the same held-out test set. The proposed Hybrid SVM outperforms all other models in terms of successfully achieving the very highest accuracy of 77.55% and the highest recall of 75.30%, highlighting the necessity of feature fusion.

Table 2: Comparative Performance of All Classifiers on the Test Set

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Naive Bayes (TF-IDF)	66.50	67.20	66.50	66.10
Logistic Regression	73.40	73.90	73.40	73.20
Random Forest	72.10	72.80	72.10	71.90
SVM (TF-IDF Only)	75.30	75.80	75.30	75.10
Hybrid SVM Proposed	77.55	74.83	75.30	74.87

Ablation Study

An ablation study conducted on the three variants on the split of same data gives the results as shown in Table 3. It is evident that the hybrid fusion outperforms TF-IDF features alone by 2.25% in accuracy and NRC features alone by 16.35%.

Table 3: Ablation Study - Contribution of Individual Feature Modalities

Feature Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
NRC Emotion Features Only	61.20	60.80	61.20	60.40
TF-IDF Features Only	75.30	75.80	75.30	75.10
Hybrid (TF-IDF + NRC)	77.55	74.83	75.30	74.87

Performance Evaluation on a Class Level Basis

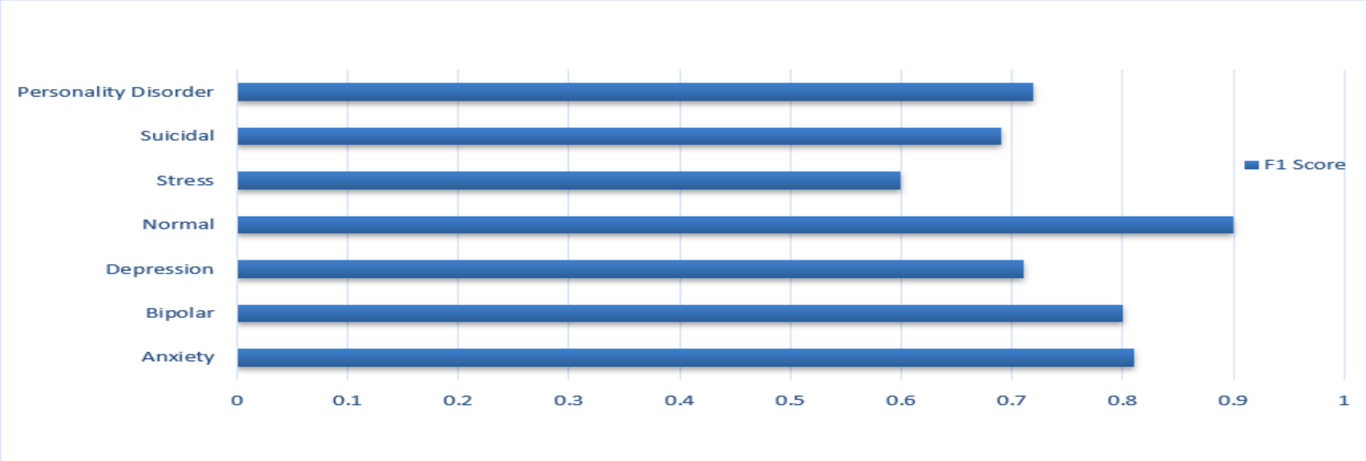

Figure 3: Class-wise F1-Score for Proposed Hybrid SVM Classifier

Table 4: Detailed Per-Class Classification Report (Actual Test Set Results)

Class	Precision	Recall	F1	Support	TP Rate	Observation
Anxiety	0.77	0.85	0.81	768	85%	High recall
Bipolar	0.81	0.80	0.80	555	80%	Well balanced
Depression	0.78	0.66	0.71	3081	66%	Low recall
Normal	0.89	0.92	0.90	3269	92%	Best class
Personality Disorder	0.77	0.68	0.72	215	68%	Minority class
Stress	0.57	0.63	0.60	518	63%	Weakest overlap
Suicidal	0.66	0.73	0.69	2130	73%	Good recall critical
Weighted Avg	0.78	0.78	0.77	10536	-	Final test result

The per-class classification results are represented through Figure 3 and Table 4 for the actual test run. The Normal class has the very highest F1 score of 0.90, as it has the number of highest samples (3,269) also unique linguistic characteristics. Anxiety and Bipolar have F1-scores of 0.81 and 0.80 respectively. Depression and Personality Disorder have 0.71 and 0.72 respectively. Stress has the lowest F1 score of 0.60, owing to semantic confusion with Anxiety and also being supported by fewer samples (518 samples). Suicidal has an F1 score of 0.69, having high recall (0.73).

VI. DISCUSSION

There are several significant advantages of the Hybrid SVM model. First, combining complimentary feature modalities leads to consistent improvements in performance over each of the baseline single-modality models, thus, confirming the hypothesis of complementarity between statistical lexical features and affective features. Second, Linear SVC + Calibrated Classifier CV provides meaningful class level confidence scores useful for clinical triage prioritisation. Third, the class balancing algorithm provides some balance correction, as seen by the F1 score of 0.72 for Personality Disorder which is quite reasonable even with a small number of test cases (215). Some limitations of the approach are the misclassification between semantically close classes (Depression and Stress; Depression and Suicidal), which can be attributed to their high lexical similarity. The training time (639.11 min) is relatively long for quick retraining related grid search procedure, but this is one of the limitations. Future research could include the importance of context aware embeddings (BERT, RoBERTa) [7], [8], [9] as one of the fusion features, SMOTE over-sampling for minority classes and multi-label classification for comorbid patients.

VII. CONCLUSION

In this work, I have developed a framework called the Hybrid Feature Fusion approach for multi-class psychological behaviour classification using support vector machine. The hybrid approach utilizes the complementary capabilities of both distributional (TF-IDF) and affective (NRC) features to provide insights into psychological language not available otherwise. Results of our experiment on a 52,680 samples with seven classes reveal that the proposed hybrid SVM classifier gives an accuracy of 77.55% and F1 score of 74.87%. Moreover, the five-fold cross-validation test reveals that our model attains a stable accuracy of 75.63% (Std = 0.49%). Ablation analysis reveals that the affective features contribute an additional 2.25% to the model accuracy. Our system is implemented as a real-time streamlit application that provides confidence scores per class in the psychological behaviour classification task. We have introduced a lightweight and easily interpretable solution to multi-class classification of psychological behaviours, thus addressing the limitations of computationally expensive approaches like deep learning models. Future scope includes transformer-based contextualized embeddings [7], [8], cross-language implementation for regional Indian languages and prospective clinical validation by domain experts.

REFERENCES

[1] Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. Journal of Language and Social Psychology.
[2] Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word-emotion association lexicon. Computational Intelligence.
[3] Coppersmith, G., Dredze, M., & Harman, C. (2014). Quantifying mental health signals in Twitter. Proceedings of the ACL Workshop on Computational Linguistics and Clinical Psychology
[4] Gkotsis, G., Oellrich, A., Velupillai, S., Liakata, M., Hubbard, T. J., Dobson, R. J., & Dutta, R. (2017). Characterisation of mental health conditions in social media using Informed Deep Learning. Scientific Reports.
[5] Yates, A., Cohan, A., & Goharian, N. (2017). Depression and self-harm risk assessment in online forums. Proceedings of EMNLP 2017.
[6] Shen, G., Jia, J., Nie, L., Feng, F., Zhang, C., Hu, T., & Zhu, W. (2017). Depression detection harvested from social media: A multimodal dictionary learning solution. Proceedings of IJCAI.
[7] Nguyen, T., Phung, D., & Venkatesh, S. (2022). Improving identification of mental health disorders using BERT-based pre-trained language models.
[8] Ji, S., Zhang, T., Ansari, L., Fu, J., Tiwari, P., & Cambria, E. (2022). MentalBERT: Publicly available pretrained language models for mental healthcare. Proceedings of LREC 2022.
[9] Lin, C., Xu, Z., Liang, B., Gui, L., & Xu, R. (2023). Multi-task learning with multi-head attention for multi-class mental health classification. Neural Networks.
[10] Yadav, S., Chauhan, J., Saha, S. K., Bhatt, J., Shrivastava, M., & Kumaraguru, P. (2020). Identifying depressive symptoms from tweets: Figurative language enabled multitask learning framework. Proceedings of COLING 2020.
[11] Agrawal, A., & An, A. (2012). Unsupervised emotion detection from text using semantic and syntactic relations. Proceedings of the IEEE/WIC/ACM International Conferences on Web Intelligence.
[12] Trotzek, M., Koitka, S., & Friedrich, C. M. (2018). Utilizing neural networks and linguistic metadata for early detection of depression indications in text sequences. IEEE Transactions on Knowledge and Data Engineering.
[13] World Health Organization. (2022). World Mental Health Report: Transforming Mental Health for All. WHO Press, Geneva.
[14] Salton, G., Wong, A., & Yang, C. S. (1975). A vector space model for automatic indexing. Communications of the ACM.
[15] Mamatha et al. (2026). Self-explanatory machine learning for disorder-type classification from behavioural and psychological data (AdaBoost, SHAP, PDP, ICE).
[16] Lamiya, H. R. et al. (2025). Personality prediction using the Myers-Briggs Type Indicator (MBTI) and NLP on real-time key logged text data, using transformer-based language models.

[17] Panchadhyayee, S. et al. (2025). A multimodal framework integrating questionnaire responses, audio sentiment analysis, and facial expression analysis (Random Forest, OpenCV, dlib, NLP) for human behaviour examination.
[18] Priyanka, R. M., & Chouhan, A. S. (2025). Predictive modelling of electronic gadget addiction among students using machine learning. International Journal of Creative Research Thoughts (IJCRT), 13(6), ISSN 2320-2882.
[19] Vlasiu, A. R., Frincu, M. E., Daniel, C., Mocan, D., & Gabor, M. (2024). Classifying mental disabilities from virtual reality behavioural data using machine learning. 2024 E-Health and Bioengineering Conference (EHB).
[20] Sa, A. P. V. et al. (2023). Machine learning-based prediction of adolescent behaviour using the WHO Global School-based Student Health Survey dataset (Naïve Bayes, SVM, Decision Tree, Random Forest, XGBoost).
[21] Kotenko, I. et al. (2021). Predicting mental states from social network (Reddit) data using Latent Dirichlet Allocation (LDA) and a fastText classifier.
[22] Lima, A. C. E. S. et al. (2016). Predicting temperament from Twitter data using David Keirsey's temperament model and machine learning.

.