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Detection and forecasting of mental health disorders using machine learning models on social media data

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ABSTRACT

The detection and classification of depression and other mental disorders have become crucial in the modern era, particularly with the growing reliance on social media for self-expression. Existing systems often face challenges like limited prediction accuracy, difficulty forecasting future mental illnesses, and handling both clinical and non-clinical data. This study proposes a novel analytical model that not only screens individuals' current mental health status from social media content but also predicts the likelihood of future mental health issues. The proposed methodology integrates classical machine learning (ML) models, ensemble learning approaches, and pretrained models for enhanced detection and forecasting accuracy. The outcome shows that pre-trained language models accomplished maximized F1-score and overall performance significantly better than conventional ML and ensemble models. The system outperforms existing methods with a significant accuracy improvement, achieving 90.9% overall accuracy, a 7.2% improvement over traditional ML classifiers, 5.8% over ensemble models, and 11.3% over language models.

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1. INTRODUCTION

Early detection and correct classification of depression are critical for effective intervention and treatment, as depression is the leading cause of disability globally [1]. Identifying symptoms early on provides for timely mental health care, lowering the chance of the disease worsening and perhaps leading to more serious difficulties such as suicidal ideation or long-term impairment in everyday functioning [2]–[5]. Reliable classification of depression ensures that people receive appropriate care based on the degree and type of their ailment, which improves treatment outcomes [6]. There are various limitations to existing depression detection and classification systems. One big issue is that social media data is noisy and unstructured, with colloquial language, slang, and acronyms, making it difficult to reliably diagnose depression symptoms. Many models also struggle to manage both clinical and non-clinical data, frequently missing key information from unstructured sources such as social media [7]. Furthermore, separating depression from different form of mental illnesses (viz. anxiety and bipolar disorder), remains difficult, and resulting in misdiagnosis. Many approaches fail to anticipate future mental health disorders by focusing solely on current symptoms. Finally, a lack of diverse training datasets might lead to biased or overfitted models, which reduces their reliability across populations. Artificial intelligence (AI) offers enormous potential in the early diagnosis and classification of depression, allowing for prompt therapies via analysis of varied data sources such as social media, voice, and clinical records [8]–[11]. However, obstacles include dealing with noisy, unstructured data, combining clinical and non-clinical information, and guaranteeing model generalizability across varied populations. Furthermore, identifying depression from other mental health diseases remains challenging, and forecasting future mental health concerns is a constantly developing task [12]–[16]. Overcoming these problems will increase the accuracy and effectiveness of AI-powered systems.

The related work carried out towards this direction are as follows: Kim *et al.* [17] developed a classification model based on textual elements from social media posts and achieved significant accuracy in diagnosing depressed symptoms, demonstrating the promise of unstructured data for mental health applications. Mountzouris *et al*. [18] investigated the use of deep learning (DL) models, specifically convolutional neural networks (CNN), to detect sadness from speech and text data. Kabir *et al*. [19] proposed using natural language processing (NLP) and machine learning (ML) approaches to detect depression-related terms in posts. Myee *et al*. [20] suggested a hybrid model that uses ML and DL approaches to identify depression in user-generated content on social media platforms. Sofia *et al.* [21] demonstrated the potential of DL for modeling complicated relationships in data for improving depression identification using unsupervised DL models, with feature extraction and representation learning playing critical roles. Xu *et al.* [22] suggested a ML-based approach for diagnosing depression in clinical settings by analyzing structured data such as medical records. Amanat *et al*. [23] used recurrent neural networks (RNNs) to classify depression from text-based data in social media forums. Wang *et al.* [24] investigated the integration of AI and wearable technologies for depression diagnosis. They created a system that detects depressive states in real time by merging physiological inputs with ML algorithms, revealing the promise of wearable technology in mental health monitoring. Lin *et al.* [25] investigated speech-based depression detection with deep neural networks (DNNs). Their research shown that DNNs may efficiently capture small vocal cues associated with sadness, providing a non-invasive way for early diagnosis in clinical settings. Hadzic *et al.* [26] used transfer learning to detect depression in text data, fine-tuning a pre-trained language model known as bidirectional encoder representations from transformers (BERT). This strategy considerably increased the accuracy of text-based depression diagnosis, demonstrating the use of transformer models in mental health applications.

The research problems in depression identification utilizing AI, ML, and DL include the difficulty of effectively reading unstructured, noisy data from social media and other informal sources, which frequently results in misclassification. Another problem is that existing models cannot properly combine both clinical and non-clinical data, limiting the scope and accuracy of predictions. Furthermore, the lack of vast, diverse, and representative datasets adopted for training models leads to biased or overfitted systems, which reduces their generalizability across populations. Models also have difficulty distinguishing between depression and other mental health problems, which leads to misdiagnoses. Furthermore, while existing methods focus on recognizing current symptoms, predicting future mental health difficulties remains a difficult challenge that necessitates more sophisticated forecasting models.

The proposed study aims for creating an innovative analytical framework that not only detects depression but also predicts the likelihood of future mental health concerns (bipolar disorder, anxiety, and attention deficit hyperactivity disorder (ADHD)) using social media data. This approach seeks to provide a comprehensive and efficient tool for detection and monitoring of mental health disorders in early stage using an individual's social media information. The study addresses the difficulty of diagnosing mental diseases in both clinical and non-clinical situations, broadening the scope of mental health research beyond typical clinical data. The notable contribution of proposed study is as follows: i) the presented model introduces a two-step classification strategy that combines ML and language model techniques to assess both the current and future mental health condition of individuals using social media posts; ii) unlike existing methodologies that largely focus on clinical data, the proposed study explores both clinical and non-clinical social media situations. This allows for a more thorough knowledge of mental health; iii) a fundamental feature of the proposed system is its ability to foresee potential mental health concerns in the future, rather than simply recognizing existing conditions; iv) the study provides more accuracy through thorough data preprocessing, such as removing noise, standardizing language, and translating data into feature representations; and v) the suggested system is evaluated using accuracy, F1-score, and precision. It beats previous algorithms in predicting future mental health disorders and diagnosing depression. The consecutive section discusses about adopted research methodology towards its implementation.

2. METHOD

The methodology used in this work attempts to create an effective system for diagnosing and forecasting mental health disorders, such as depression, using social media data as shown in Figure 1. The approach begins with the acquisition of a broad dataset from clinical and non-clinical social media contexts, which is then preprocessed and text normalized to improve data quality. Feature extraction is carried out with advanced techniques such as term frequency and inverse document frequency (TF-IDF) for conventional ML framework along with embedding vectors for language model approaches. Finally, a two-step classification technique is used, combining several ML and language models to improve predictive accuracy and predict future mental health difficulties.

Figure 1 elaborates a detailed workflow that begins with text preprocessing followed by extraction of significant features adopting TF-IDF towards conventional ML models while pre-trained language models is used for contextual embedding. The initial stage detects existing disorder while the secondary stage predicts the upcoming threats depending upon social and temporal behavior. The model also combines multiple classifiers e.g. BERT, robust bidirectional encoder representations from transformers (RoBERTa), gradient boosting, random forest, and logistic regression adopting ensemble strategy of hard voting. This offers an assurance towards strengthening of each framework towards optimal performance gain.

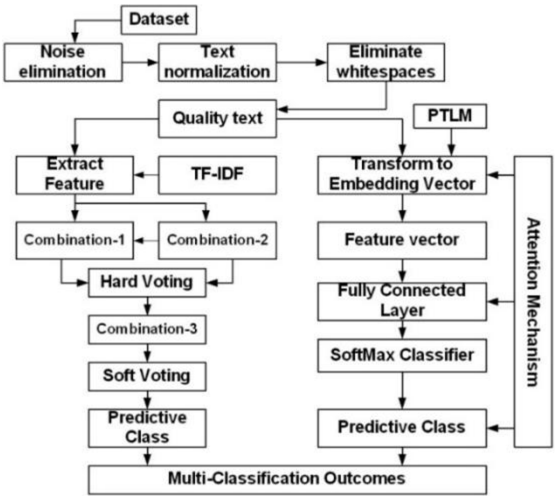

Figure 1. Comprehensive evaluation platform for diagnosis depression

2.1. Data aggregation with preprocessing

The preliminary implementation stage is to collect publicly available data about mental health derived from social media. The dataset will include social media posts from platforms like Reddit, Twitter, and other online forums, with a focus on information related to depression, bipolar disorder, anxiety, and ADHD. Each post is a text document that must be processed and prepared before further investigation. Let $D = \{d_1, d_2, \ldots, d_N\}$ represent the dataset with N documents (social media posts). Each document di is processed to extract features. $F_i = \{f_1, f_2, \ldots, f_m\}$, where m is the number of preprocessed words or tokens. The acquired data goes through many preprocessing processes (stopword removal, tokenization, text normalization, and noise elimination) to assure its quality and eliminate noise, which can have a detrimental influenced on the performance of the framework.

It should be noted that clinical data refers to the post of social media that discretely mention condition of mental health, treatment, as well as symptoms. For an example: "I was diagnosed with depression last year" or "My doctor recommended medication for depression." On the other hand, the non-clinical data involves everyday social post that may showcase states of mental health indirectly e.g., "I feel non-energetic to work" or "I couldn't get better sleep". Inclusion of these two classes permits the system to learn patterns of subtle behavior and learn overt associated with mental well-being.

2.2. Feature extraction

The preprocessed data is required to be suitable for ML-friendly format. We use two main feature extraction methods: TF-IDF for ML and embedding vectors for language modeling. This method is a statistical measure that evaluates the significance of a terms present in a document in relation to a larger corpus of information. The mathematical formulation for TF-IDF is provided by (1).

$$TF - IDF(w, d) = TF(w, d) \times IDF\ (w) \tag{1}$$

As in (1), the computation of first and second component is carried out as follow: $TF(w, d) = \frac{count(w,d)}{\sum_{i-1}^{m} count(w,d)}$ and $IDF(w) = log\left(\frac{N}{DF(w)}\right)$ respectively. The first component TF(w,d) represents term w frequence present in d document while IDF(w,d) represents inverse document frequency for w words while DF(w) represents quantity of document while N is total documents. DL-based algorithms use pre-trained language models to convert each post into a word embedding vector. These models transform each word or sentence into a continuous vector containing semantic associations. Passing a document d_i through a pre-trained language model yields the embedding vector E_i. The embedding vector captures more semantic information than basic frequency-based approaches such as TF-IDF.

2.3. Model design and classification

During the classification phase of the process, various ML and language models are trained to predict the severity of depression and other mental health conditions. Two sorts of classification are used: classification of current disorder status and predicting of future mental health status. The suggested system utilizes various ML models logistic regression, support vector machines, random forests, k-nearest neighbors, and gradient boosting. We use language models to gain a greater knowledge of semantics. The output of these models, an embedding vector E_i, is fed into a classification layer to forecast the likelihood of each class. The model predicts $P(c|d_i)$ based on the post di, with c representing the class (e.g., depression and anxiety). A SoftMax function determines the language model's output for each class.

$$P(c|d_i) = \frac{e^{f(c,d_i)}}{\sum_{c'} e^{f(c',d_i)}} \tag{2}$$

According to (2), the score of class c for document di is represented by $f(c,d_i)$, whereas $P(c|d_i)$ provides the probability distribution across all possible classes. After training multiple models, we use dual-class classification viz. i) current disorder prediction for identifying mental health condition (e.g., depression and anxiety) and ii) forecasts future mental diseases using history posts and identified patterns. To improve prediction accuracy, we employ techniques of ensemble learning (hard voting and stacking). The hard voting approach involves numerous classifiers voting on the predicted class, and the class with the highest number of consensuses is chosen as the end-level prediction.

3. ACCOMPLISHED RESULTS

The simulations are carried out on a high-performance server with strong hardware specs. The server had an Intel Xeon Silver 4210R CPU with 10 cores hosted at a base frequency of 2.40 GHz and an NVIDIA Tesla T4 GPU with 16 GB of VRAM, allowing for faster training of language models including BERT, RoBERTa. In addition, the server contained 64 GB of DDR4 RAM and a 2 TB SSD for quick data retrieval and model checkpoint storage. These criteria enabled the efficient processing of enormous datasets, guaranteeing that model training and testing were completed within tolerable time constraints, especially when dealing with sophisticated models such as language models and ensemble learning techniques. The software stack operated on Ubuntu 20.04 LTS where Python 3.8 is used in form of programming language. Several libraries and frameworks were used, including scikit-learn for implementing classical ML models like logistic regression method, support vector machine, and k-nearest neighbors; TensorFlow and PyTorch for training and fine-tuning language models like BERT, RoBERTa; and XGBoost and LightGBM for ensemble learning. Natural language toolkit (NLTK) and spaCy handled text preprocessing and feature extraction. Further, the model uses Hugging Face's Transformers Library to give easy access to standard pretrained models. Finally, Matplotlib and Seaborn were utilized to visually represent model performance metrics and F1-scores.

To detect contemporary mental diseases (depression, anxiety, bipolar disorder, and ADHD), the models were taught to categorize social media posts. Using standard dataset [27], the findings are described in Table 1, which shows the average F1-score for each disease across all models. The first objective of the study is to determine the present state of mental disorder originating from the social media post while the second objective emphasizes on predicting the probability of issues related to mental health in future based on behavior of previous social media post. The numerical outcomes of both these objectives are shown in Table 1 as well as Table 2.

The accomplished outcome acquired Table 1 as well as it is represented in Figure 2 infers following: BERT and RoBERTa consistently performed the best across all mental diseases, with F1-scores whose numerical values resides between 0.79 to 0.81. These models revealed a higher ability to comprehend and categorize the intricate material associated with mental health issues. Both logistic regression and random forest fared well, with average F1-scores of 0.69 and 0.72, respectively. These models were especially good at recognizing depression and bipolar disorder, which are more openly expressed in social media posts. K-nearest neighbors obtained the lowest F1-score for detecting ADHD and anxiety, indicating its limits in analyzing complex mental health-related texts.

Table 1. Performance of different models for current disorder detection

Model	Depression (F1)	Anxiety (F1)	Bipolar (F1)	ADHD (F1)	Average F1
Logistic regression	0.72	0.68	0.70	0.66	0.69
Support vector machine	0.68	0.64	0.69	0.63	0.66
K-nearest neighbors	0.45	0.41	0.48	0.37	0.43
Random forest	0.72	0.70	0.74	0.71	0.72
Gradient boosting	0.71	0.69	0.73	0.70	0.71
BERT	0.80	0.77	0.79	0.75	0.78
RoBERTa	0.81	0.78	0.80	0.76	0.79

Table 2. Performance of different models for future disorder prediction

Model	Depression (F1)	Anxiety (F1)	Bipolar (F1)	ADHD (F1)	Average F1
Logistic regression	0.66	0.61	0.64	0.58	0.62
Support vector machine	0.63	0.58	0.62	0.57	0.60
K-nearest neighbors	0.41	0.36	0.43	0.31	0.38
Random forest	0.68	0.65	0.69	0.63	0.66
Gradient boosting	0.67	0.63	0.68	0.62	0.65
BERT	0.74	0.70	0.73	0.68	0.71
RoBERTa	0.76	0.72	0.75	0.71	0.73

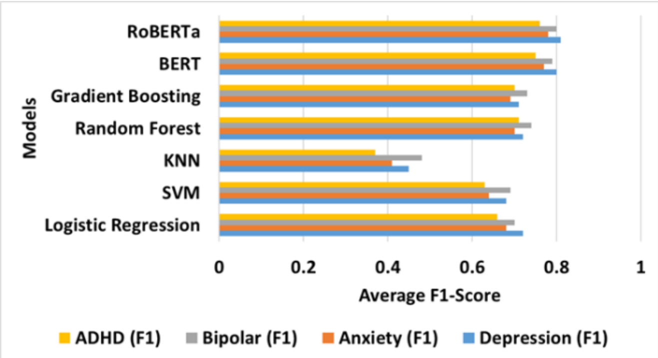

Figure 2. Visual outcomes for of different models for current disorder detection

The outcome obtained in Table 2 and Figure 3 infers following: RoBERTa outperformed other models in forecasting future diseases, with an average F1-score of 0.73. It is seen that random forest and gradient boosting performed well at predicting future disorders, with average F1-scores of 0.66 and 0.65, respectively. K-nearest neighbors scored badly, particularly in predicting future mental health disorders.

Figure 4 showcase the finally accomplished study outcomes. Figure 4(a) shows outcome with respect to depression exhibiting RoBERTa to accomplish maximum F1-score of 0.81 showing increased predictive capability and strong detection. Figure 4(b) shows outcome with respect to anxiety stating similar performance for BERT and RoBERTa; however, RoBERTa performs slightly better towards future prediction. Figure 4(c) exhibits outcome for bipolar exhibiting potential performance for random forest and BERT; however conventional ML models outperformed language models. Finally, Figure 4(d) exhibits outcome for ADHD to exhibit accurate detection with RoBERTa.

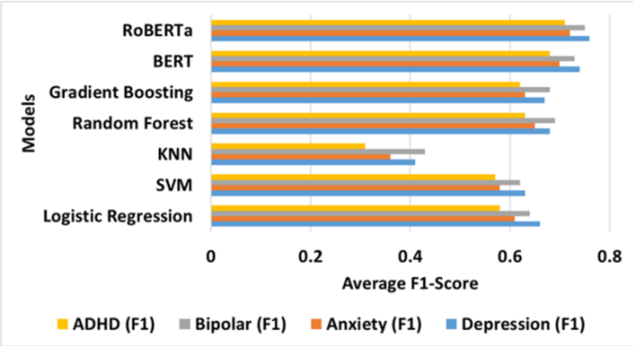

Figure 3. Visual outcomes for of different models for future disorder detection

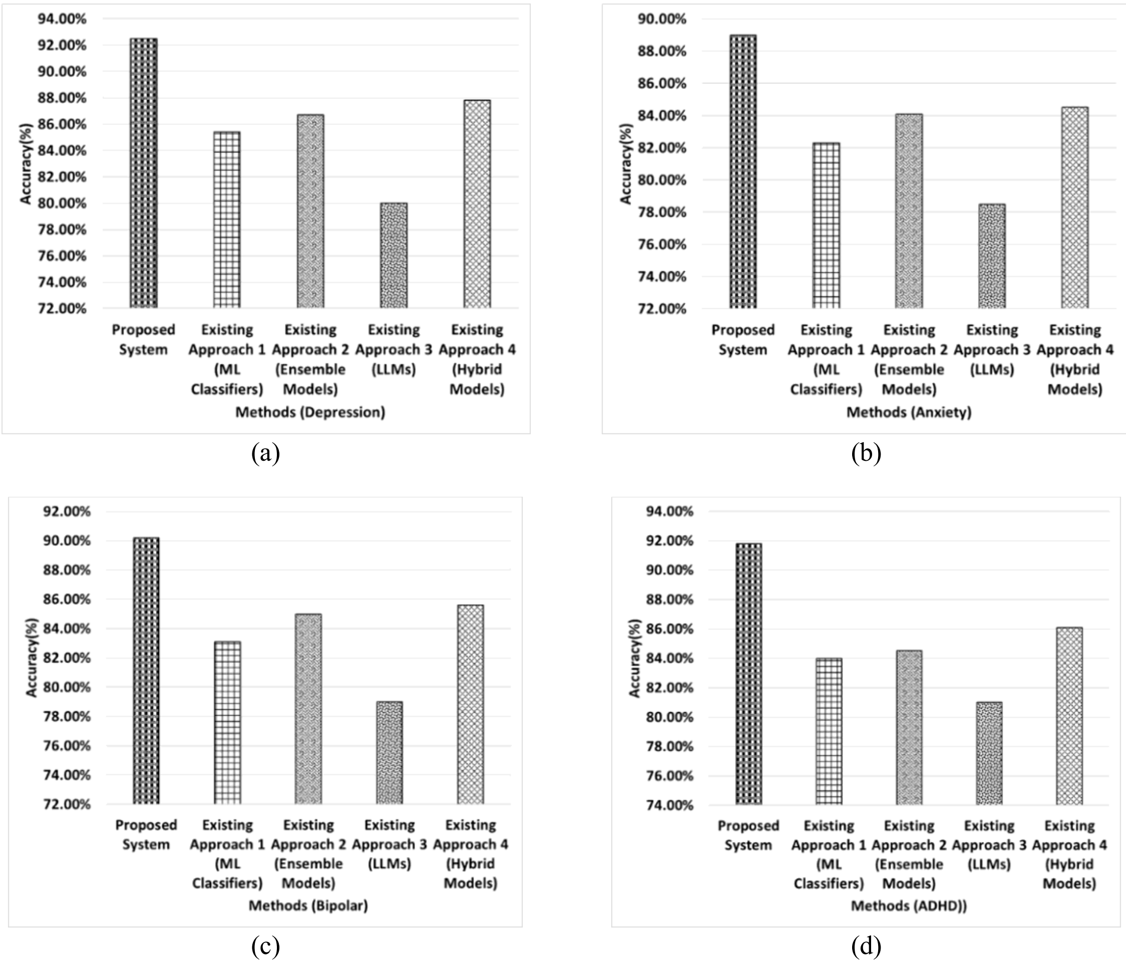

Figure 4. Accomplished accuracy results of (a) depression, (b) anxiety, (c) bipolar, and (d) ADHD

The results exhibit suggested approach is superior at detecting and forecasting mental diseases from social media data. The suggested technique has an average accuracy of 90.9%, exceeding all known approaches for all illnesses. It outperforms existing approaches 1 (ML classifiers) by 7.2%, 2 (ensemble models) by 5.8%, and 3 (LLMs) by 11.3%. The hybrid models likewise indicate a 4.9% improvement over the intended system. These findings support the usefulness of an integrated method that integrates numerous ML models, ensemble approaches, and language models, resulting in much higher prediction accuracy.

The overall discussion of the accomplished outcome is as follows: unlike existing systems that focus only on detecting mental health disorders originating from contents in social media, our model incorporates both detection and prediction aspects. It not only identifies whether an individual is currently affected by a disorder, but also forecasts the possibility of future mental health conditions based on past behavior and trends in social media interactions. The contribution of the presented model is the ability to analyze both clinical (data involving discussions of mental health) and non-clinical data (everyday social media conversations). By extending the scope to include non-clinical data, the model gains extensive, and comprehensive understanding of mental condition of an individual, improving prediction accuracy and broadening the range of users it can assist. The suggested system utilizes a novel two-step categorization method. The initial stage is to convert text input into TF-IDF features for traditional ML models, and embedding vectors for DL-based models (language models). The second stage uses a hard voting technique with many classifiers to improve forecast accuracy. The joint usage of ML and DL models ensures robustness by using each model's strengths. The system outperforms typical ML models by using ensemble learning approaches (e.g., bagging, XGBoost, and LightGBM), as well as pre-trained language models such as BERT and RoBERTa. The voting process enhances prediction accuracy by reducing the possibility of false negatives and ensuring that people who are at risk of mental illness receive prompt assistance.

4. CONCLUSION

This study describes a comprehensive and new strategy to detecting and forecasting mental diseases, specifically depression, anxiety, bipolar disorder, and ADHD, using social media data. This work's significant accomplishments include creation of a two-step classification model that combines conventional ML approaches with cutting-edge language models to boost detection and prediction accuracy. The proposed system not only effectively identifies individuals currently experiencing mental health disorders using both clinical and non-clinical social media data, but it also predicts the occurrence of these disorders in the future, representing a significant advancement in early mental health intervention. The hybrid technique that blends ML and language models, as well as the hard voting mechanism that aggregates the strengths of numerous models to produce improved predictive accuracy, make this work unique. By taking into account both clinical and non-clinical situations, this study expands the scope of mental health analysis beyond standard clinical settings, shaping it more suitable to real-world circumstances. Furthermore, the capability of system to identify probable future mental health disorders provides a preventative dimension to mental health diagnosis, with the potential to dramatically improve therapeutic tactics. Future study will concentrate on enhancing the model by including new data sources such as photos and videos, hence increasing accuracy. Furthermore, ethical concerns about the utilization of data derived from social media for mental health predictions will be subjected to stronger privacy safeguards and adherence to data privacy legislation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Narve Lakshminarayan Taranath	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declares that current work has no conflict of interest with any other existing works.

DATA AVAILABILITY

The data leveraging the outcome of this present work can be made available by contacting the corresponding authors, [CIV], stating justified reason of its usage.

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