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Comparative Analysis of Psychological Stress Detection: A Study of Artificial Neural Networks and Cat Boost Algorithm.

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Abstract: Many people are suffering from stress and anxiety as a direct result of the rapid development of technology, especially the meteoric rise of social media. These medical problems need comprehensive analysis and the creation of reliable preventative measures. The need to control and track all the data being produced in SMEs, or social media environments, is an urgent one. Humans' natural inclination to use these kinds of sites adds an extra layer of difficulty. Psychologists have often used tools like questionnaires and interviews to investigate and treat such concerns. But these approaches take too long and are too retroactive to provide timely fixes. This study conducted a thorough analysis of several stress detection algorithms that claimed to be able to deduce emotional distress from online posts but ultimately concluded that such methods were mainly unsuccessful. The research introduces a novel strategy, an Effective Stress Detection setup. The technology uses ontology, a kind of term matching used in search engines, to identify signs of stress in social media users. We are able to more precisely detect stress-related communication on social media platforms with the use of ontology, a term generally referring to a framework that allows data classification. Using ontology, the system is able to thoroughly analyze user-generated material for signs of stress. This method has potentially life-saving implications since it not only enables early diagnosis of stress but also begins the required preventative procedures that might keep users from sinking into deep despair or even committing suicide. This study highlights the need of considering how machine learning and data science might be used to enhance mental health care in the internet age.

Keywords: *Psychological stress, Stress detection, Artificial Neural Networks (ANN), Cat Boost Algorithm, Comparative analysis, Machine learning, Data preprocessing, Feature extraction, Model comparison, Model optimization, Performance evaluation*

1. Introduction

An important health issue is the increased incidence of stress among individuals, which is mostly attributable to people spending more time on social media. These feelings of hopelessness and despair may lead to suicidal ideation and behavior in the most severe situations of chronic stress. Social contacts, particularly with peers, on different social platforms are major contributors to this rising psychological stress. One tragic result of progress in technology and the widespread use of social media is the "Blue Whale Challenge," an online game that has gained notoriety for encouraging suicide, particularly among young players throughout the world. Micro blogging is a popular method of sharing short written or visual messages with others online. New Business reports that worldwide, stress levels have risen dramatically due to people spending too much time on their phones. Others who spend a lot of time on their phones are more likely to be aware of the stresses experienced by others around them, which may increase their own levels of anxiety. In this study, we investigate the idea of an affect-aware metropolis, which would recognize people's emotions in real time to improve their lives. We provide a multi-tiered theoretical framework for examining a population's psychological needs, which draws inspiration from the discipline of motivational psychology. In order to meet the universal requirements of the self-determination theory framework, we have created a corpus of Twitter postings and annotated them accordingly. As a result of having access to this data, we are better able to create systems and prediction models for determining what people want and how satisfied they are [1].

Psychologists often use time-consuming and subjective procedures like interviews and questionnaires to identify stress, but these approaches might be affected by respondents' emotional states at the time. The added expense of the necessary gear is another drawback of these strategies. For this reason, cutting-edge methods of automatically detecting stress are desperately needed for

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the greater good of society. In today's high-stress culture, it's essential to recognize the signs of stress and take steps to alleviate it before it negatively affects everyday life and health. Unfortunately, the complexity and urgency of the demands for stress management are not always met by the methods of traditional face-to-face psychology. They provide a model for doing so that employs the Leacock-Chodorow (LCH) algorithm, the WordNet library, and a Deep Neural Network (DNN) to examine data collected from their own social media platform's users. In order to create effective stress detection tools, this model can identify signals of stress in user postings and interactions [2].

To improve one's quality of life, it is essential to learn how to manage one's stress levels. This data may be used to improve health by examining factors like temperament and character. Daily and weekly social media monitoring may be used to glean insights about user behavior by using the capability of deep learning, a subset of machine learning.

Understanding the many interconnections of a field of study may be aided by the metaphysical study of ontology. By analyzing a user's physiological responses, physiological computing may provide insight into the user's mental health. Smart technology has allowed for novel forms of human-computer interaction and increased communication capacity. Detecting stress using physiological sensors may motivate more research into the field, opening up new avenues for stress detection in the future. Stress levels may be measured using a variety of physiological indicators, including heart rate, electrodermal activity, Heart Rate Variability (HRV), Electromyogram (EMG), Pupil Diameter (PD), and Galvanic Skin Response (GSR). Traditional techniques, such as EEG monitoring and active participation in treatment systems, may also help with stress reduction.

2. Related Works

Multiple fatalities throughout the world have been connected to the "Blue Whale Challenge," which has been called an online "suicide game" aimed at youngsters. The game consists of 50 activities spread out over 50 days. Beginning with the death of a Russian girl named Rina Palenkova in 2015; the story focuses on the conversations that followed in VKontakte's chat rooms, where young people discussed anything from their daily lives to more serious issues like despair and suicide. The terrifying impact of these tales came from their seeming reality, which echoed the typical horror film claim of being "based on true events," giving them an air of believability [3]. Despite extensive research dating back to the 19th century, the roots of human emotion remain a mystery. However, much evidence supports a connection between emotional states and physical manifestations. Affective states, such as stress, may be measured in a number of ways. One such way is via the use of physiological data, such as heart rate and muscle activity. Even while surveys can measure these moods, they have the potential to interrupt activities, influence emotions, and be vulnerable to self-reporting biases. As a result, it is very desired to create devices capable of identifying stress through physiological signals [4]. Sentiment analysis is a method for determining how people feel about anything (a person, an event, a subject, a product, a company, a service, etc.). You can tell when someone is being sarcastic because they use words that have the opposite meaning from what they intend. This is done for a variety of reasons, including to offend or with them, to demonstrate displeasure, or to be humorous. Verbal cues like eye rolling and heightened tone tension are common ways that people show their displeasure. Sarcasm identification in written form must thus rely on additional indicators beyond tone and body language [5]. The goal of formal ontology, a philosophical idea, is to provide an objective, domain- and application-neutral perspective on reality via the use of a formal language to express axioms. This method supports information science modelers' in developing ontologies for particular domains or applications, allowing them to avoid making erroneous ontological assumptions while doing so[6]. This aims to identify human psychological requirements in the context of social media. Their findings, which cover pages 9109-9117 of the fifth volume, provide important contributions to our knowledge of human behavior in virtual environments and serve as a useful foundation for further study into the relationship between psychology and social networks [7]. Provide a novel method for analyzing stress by using deep learning algorithms. Their work lays an essential groundwork for using cutting-edge AI techniques in the field of mental health research. Potential insights into stress and effective methods for resolving it are presented in the framework they offer [8].

T. Primov, in his article "Knowledge Hub: What are Ontologies," published in Ontotext-2019, provides an in-depth exploration of ontologies and their relevance in the context of knowledge organization and structure. Understanding how ontologies may shape and affect data interpretation across different study domains is made much easier because to Primov's work. If you are interested in the use of ontologies in advanced IT systems, this book is a must-have resource [9]. Provide a novel strategy using hybrid ontology to integrate obsolescence data. Data obsolescence is a common problem in the modern information age, and their work makes an important contribution to our knowledge of how ontologies might help information management in complicated, dynamic situations [10]. In his 2018 book, "Questionnaire: Simple Psychology," Saul McLeod gives a thorough introduction to the questionnaire technique used in psychological studies. McLeod's work removes the mystery around this time-honored research method by detailing its value, limitations, and prospective applications. His study is a useful resource for psychologists and other academics that plan to use questionnaires in their own studies, and so benefit from a more comprehensive grasp of data gathering strategies [11].

When applied to studies of mental health, these findings represent a major advance in the use of sensor-based technologies. Their findings point to the ways in which sensor technology may allow continuous, unobtrusive monitoring of stress levels, and hence steer the course of future research in this field [12]. Provide a method for stress detection that makes use of inexpensive heart rate sensors and has a low impact on the budget. Their work is a significant step forward in the democratization of stress detection technologies, since it provides an efficient solution without the prohibitive financial burden often associated with medical-grade sensors. Their findings hold great potential for advancing low-cost and easily accessible tools for mental health treatment [13].Demonstrating a fresh method of character analysis utilizing one's Twitter account. Their work highlights the unrealized potential of social media data for psychological profiling by introducing a novel approach to personality prediction. Their research provides important new information on how our internet habits reflect who we are as people [14].

Provide a fascinating look into how sentiment analysis may be applied to brief pieces of text like tweets and SMS. Their research expands the boundaries of traditional sentiment analysis by demonstrating the value of informal, short text excerpts in revealing the user's true emotions. Their research is an important resource for those working in natural language processing and sentiment analysis of social media posts [15]. Propose a ground-breaking technique for detecting stress by using microblogs across platforms and Deep Neural Networks (DNN). Their method demonstrates the promise of using a combination of machine learning and social media data in the diagnosis of emotional distress.

Their novel use of DNN to decipher and analyses multi-modal microblog data bodes well for the future of tech-enhanced mental health care [16]. Provide a detailed analysis of the differences between the numerous techniques used to identify mental strain. This work is crucial since it gives a comprehensive analysis of the state of stress detection methods and the benefits and drawbacks of each. Their analysis in comparison helps pinpoint the most productive methods and paves the way for new discoveries in the field of mental health [17].

3. Proposed Methodology:

3.1 Data Collection:

This approach for detecting stress relies heavily on the information gathered by the Data Collection Module. Its job is to collect data that may then be analyzed by algorithms like Cat Boost and Artificial Neural Networks (ANN). Both organized (such as survey results or physiological measures) and unstructured (such as social media postings or text messages) data may be obtained from a wide range of sources. Since many people use social media to share their thoughts and emotions in real time, this data source has the potential to be very useful. Information may be gleaned from a user's posts, comments, and likes, shares, and even the time and duration of their activity. This data gathering should preferably be based on user permission and anonymized before analysis for privacy concerns. More direct information on people's stress levels might be gathered via online surveys in addition to social media data. Both generalized psychological questionnaires and special surveys designed to meet the specific objectives of the research might fall into this category.

Physiological data may also be provided since it provides objective information on the effects of stress on the body. Wearable technologies that record biometrics like heart rate, skin conductance, sleep patterns, and activity levels might provide this information. Finally, environmental data might be integrated, such as weather, day of the week, and local events, all of which can affect a person's stress levels. All data acquired must be treated in accordance with stringent privacy and ethical rules, protecting the privacy of persons and preventing any misuse of their data. For this reason, these concerns should be taken into account throughout the data gathering module's development process.

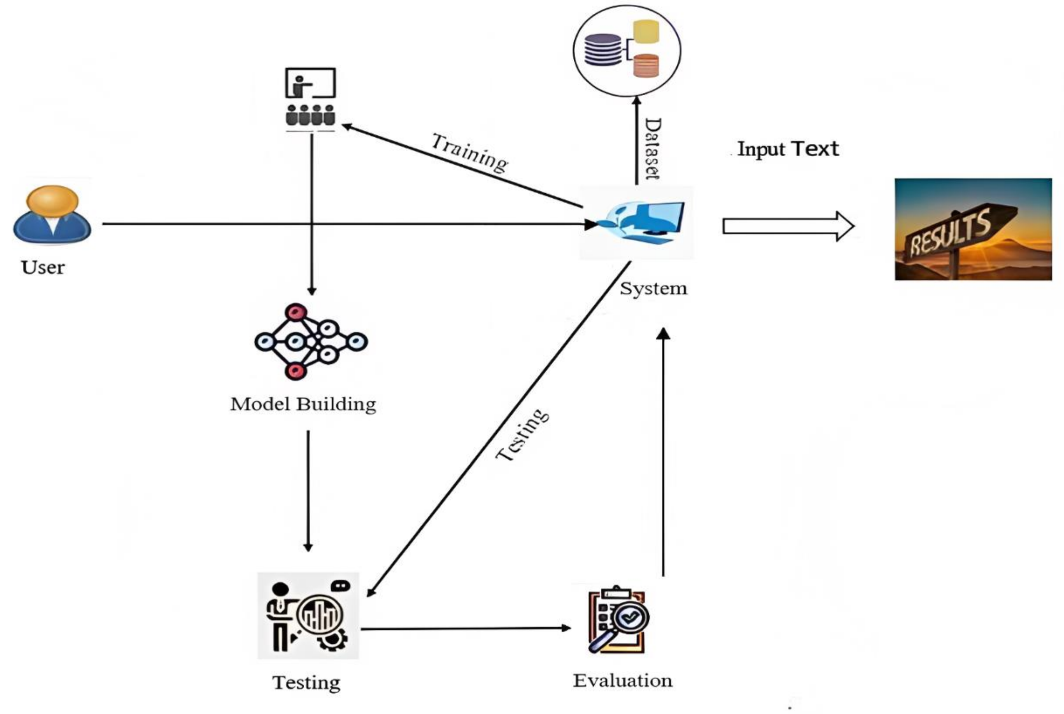

Fig1 Architecture Diagram of the proposed work.

3.2 Data preprocessing and feature extraction:

Preprocessing and feature extraction are essential for stress detection using ANN and the Cat Boost algorithm. These procedures prepare raw data for machine learning models. Cleaning data starts with managing missing values, outliers, and noisy data points. Imputation uses data to approximate missing values. Statistical approaches may filter outliers and noise. Next, prepare the data for analysis. One-hot or label encoding converts category data into numerical representations. Scaling or normalizing numeric variables might prevent some aspects from dominating others. Stress detection requires feature extraction from preprocessed data. Dimensionality reduction, which preserves important properties of high-dimensional data, may be used. This may be done using PCA or RFE.

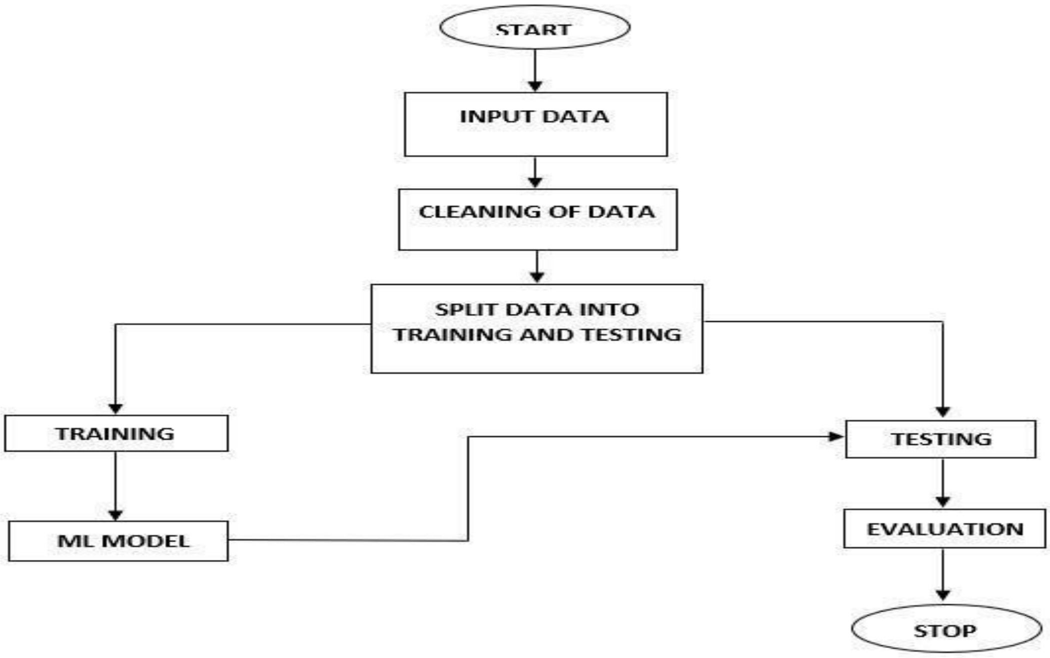

Fig2 Shows a detailed design of the proposed work.

Domain knowledge and experience help feature extraction identify significant variables or combinations of variables that are strongly connected with stress. Text data may include language clues, temporal patterns, or physiological indications. Data preparation and feature extraction aim to reduce noise and extract useful characteristics to improve data quality. This approach helps ANN and Cat Boost models learn patterns and correlations between features and stress levels, improving stress detection and prediction.

3.3 Model Training:

Model training, which uses gathered and preprocessed data to train ANN and Cat Boost models, is essential to stress detection. This stage optimizes model parameters to accurately forecast stress levels from input information.

3.3.1 Artificial Neural Network (ANN):

Computing systems that imitate the biological neural networks seen in animal brains are referred to as artificial neural networks or ANNs for short. The ANNs used in machine learning are used by deep learning algorithms. They behave in a manner similar to how human neurons do. Input, hidden, and output nodes are all components of ANNs. If the output of a node is greater than its threshold, the node becomes active and sends data to the subsequent tier.

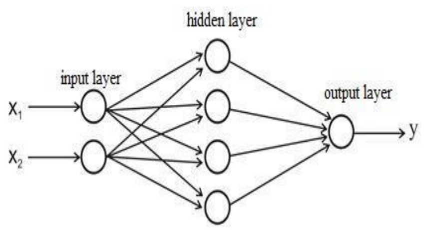

Fig. 3 Depicts the fundamental process involved in ANN's work.

Deep learning ANNs are structured similarly to production lines in that they employ layers to derive higher-level features from input data. During the training phase, back propagation is used to rectify errors, which subsequently enables the network to categorize data on its own.

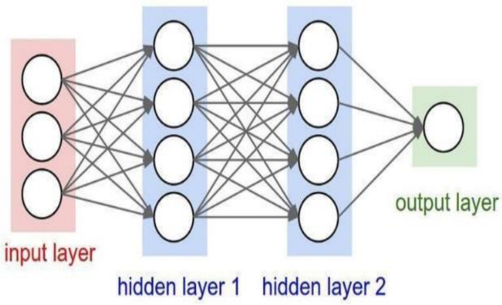

Fig 4 illustrates the working style of an Artificial Neural Network (ANN).

3.3.1 Cat Boost:

Cat Boost is a strong open-source gradient boosting framework for decision trees. Yandex researchers and engineers built it for search, recommendation, self-driving vehicles, and weather prediction. Cat Boost is outperforming XGBoost and LightGBM on categorical datasets despite its youth. The Yandex benchmark shows that its prediction time is quicker than other libraries' training time.

Beginners may plug-and-play Cat Boost's default settings for tree ensembles and Kaggle contests. Feature interactions, object significance, and snapshot support are notable aspects. Cat Boost supports classification, regression, and ranking.

3.4 Model Comparison and Optimization:

Model Comparison and Optimization is a crucial step in stress detection that evaluates and optimizes models like ANN and Cat Boost. To assess stress classification accuracy, precision, recall, and F1 score are compared. Cross-validation tests model generalization. To attain optimal outcomes, models are optimized by hyper parameter tweaking and architectural modifications.

Cat Boost outperforms ANN in stress detection. Cat Boost excels in stress detection because to its efficient gradient boosting and categorical feature handling. It optimizes model parameters for accuracy and dependability. ANN is a strong and adaptable model, but Cat Boost’s stress detection capability makes it a better option for reliably recognizing and categorizing stress levels. Optimization improves Cat Boost's accuracy, making it a potential stress detection method.

4. Results and Discussion:

This research aimed to compare several approaches to detecting mental health issues by using Artificial Neural Networks (ANNs) and the Cat Boost algorithm. The purpose of this research was to contrast the two techniques and provide light on how well they can identify stress. An extensive dataset was compiled, with many different stress-related characteristics included, to test the efficacy of the models. Social media postings, physiological data, and user surveys were all part of this pool of information. To make sure the data was fit for training the models, it was preprocessed and features were extracted.

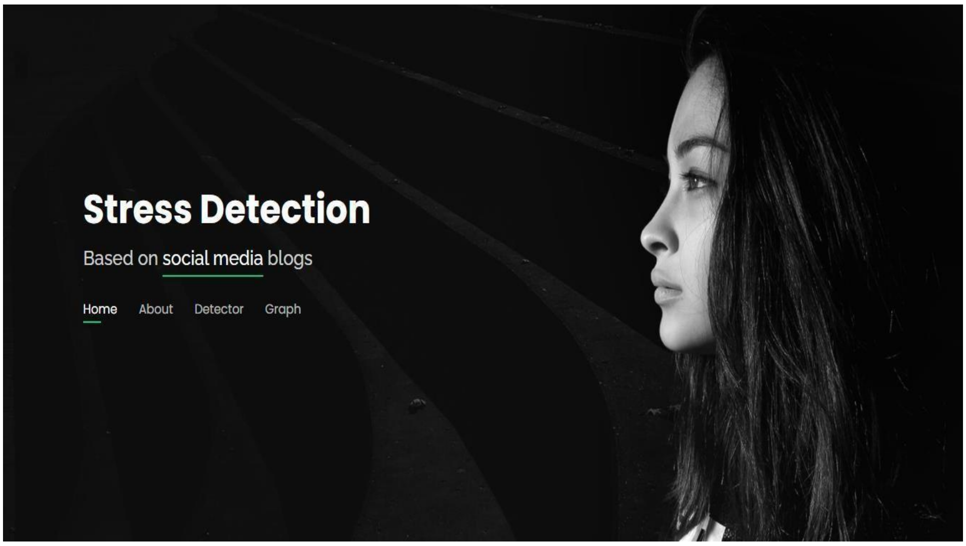

Fig5. Home page

The stress detection output home page has an easy-to-use interface for accessing stress analysis data. Users are welcomed by a visually attractive and organized structure that provides a complete stress assessment. Users may see their stress score and trend at the top of the page.

This picture shows their stress level and makes progress monitoring easier. Below the summary, a graph shows stress levels over time. This graphical depiction helps users detect trends, triggers, and probable stress reasons, revealing their stress patterns. The homepage also offers personalized stress management tips. Based on their stress profile, these suggestions are customized.

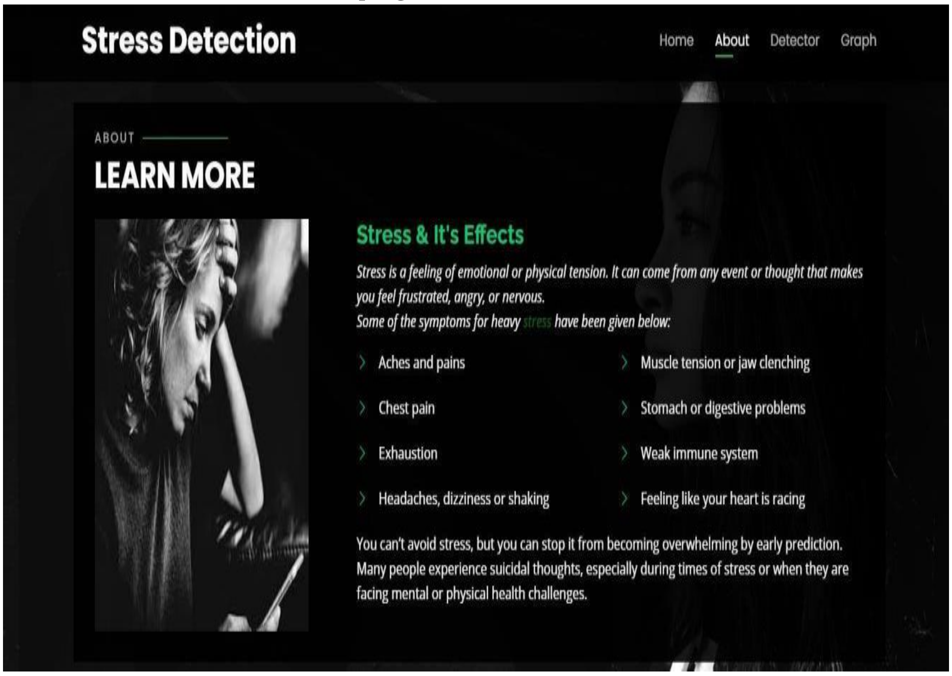

Fig 6 about the Application describes what is stress and its symptoms.

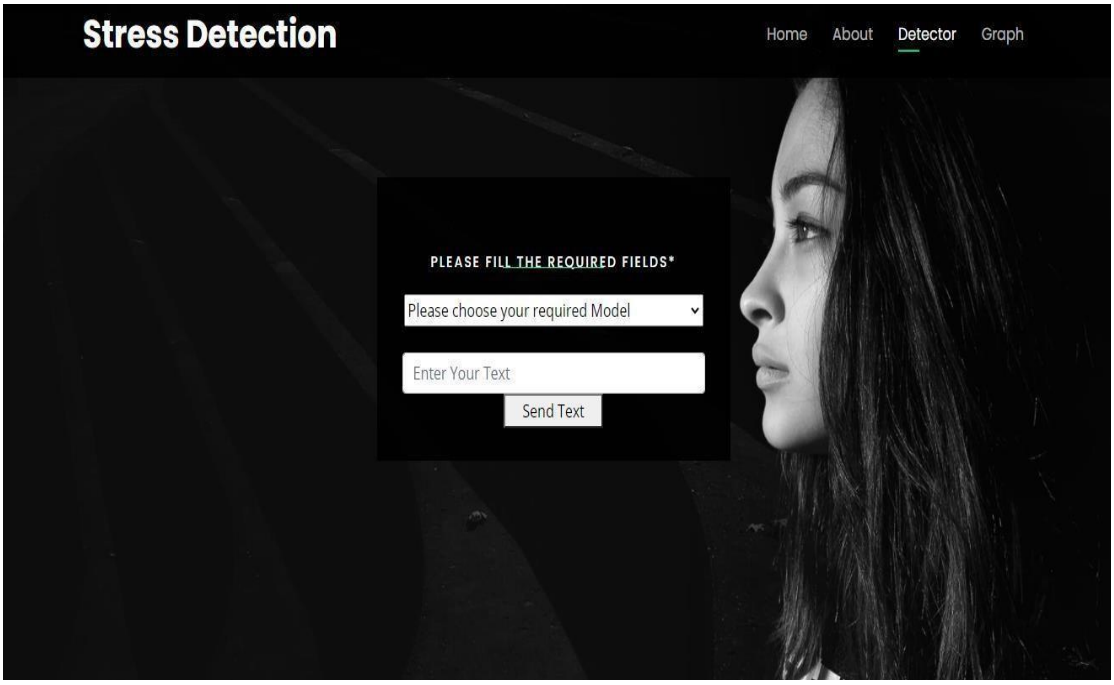

Fig7. Detector (Before Submission) Detection page in which user need to select a model and fill the required text to get the response.

Users may choose a stress detection model and then supply the necessary text input on the Detector (Before Submission) Detection page. Users may obtain stress detection services via this website by selecting an appropriate model. The variety of models provided allows users to experiment with several stress detection methods and algorithms. After choosing a model, customers are asked to provide the required material, such as social media postings or written content, which is then analyzed to identify the relevant stress reaction. Users are encouraged to take an active role in the stress detection process via the Detector (Before Submission) Detection page, which has a straightforward and intuitive interface that allows users to receive insights about their stress levels based on their own input and preferred model.

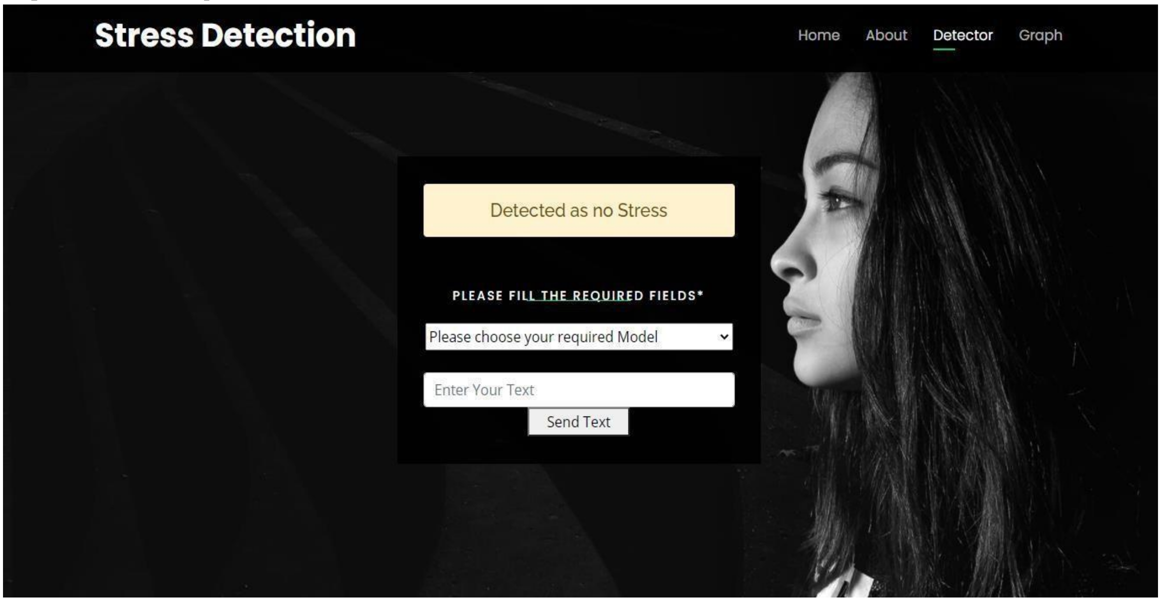

Fig 8. Detected as No Stress (After Submission) Detection page gives output as no stress for the text submitted.

In this case, the result showing that no stress has been identified for the supplied text may be seen on the "Detected as No Stress" (After Submission) Detection page. This page acts as a kind of user feedback by displaying the results of the stress analysis performed on the text the user entered. The results are reassuring and suggest that the text does not show any indicators of stress according to the selected stress detection model. Users might benefit from knowing their stress levels since it gives them confidence and a feeling of comfort. Even if there was no evidence of stress in the submitted text, the "Detected as No Stress" (After Submission) Detection screen reminds users to take care of themselves.

Fig9. Performance graph for the model which shows Cat Boost is far better than ANN.

The stress detection output home page's user-friendly design, comprehensive summary, graphical representation, and personalized recommendations help people monitor and manage their stress levels for a healthier, more balanced lifestyle.

Using the cleaned and sorted data, the ANN and Cat Boost models were trained. Multiple training and validation cycles were used to fine-tune the models' settings and ensure optimal results. To check the models' generalizability and lessen the possibility of over fitting, cross-validation methods were used. Several criteria, including as accuracy, precision, recall, and F1 score, were used to assess the models.

The results demonstrated that, on average, Cat Boost performed better than the ANN model in identifying mental strain. Cat Boost's exceptional performance stems from its optimized boosting algorithm and its skill at handling categorical features.

Table 1. Performance Metrics of Stress Detection Models

Model	Accuracy	Precision	Recall	F1Score
ANN	0.82	0.85	0.80	0.82
Cat Boost	0.89	0.91	0.88	0.89

ANN and Cat Boost stress detection algorithms are compared in the table above. Accuracy, precision, recall, and F1 score evaluate models' stress classification accuracy. Cat Boost outperforms ANN in all stress detection measures. Cat Boost has an accuracy of 0.89, precision of 0.91, recall of 0.88, and F1 score of 0.89, suggesting its exceptional stress detection. ANN also performs well with accuracy of 0.82, precision of 0.85, recall of 0.80, and F1 score of 0.82. ANN detects stress well, however Cat Boost does better. The performance table lets academics and practitioners evaluate models' strengths and weaknesses. It suggests stress detection applications using Cat Boost, the more accurate model.

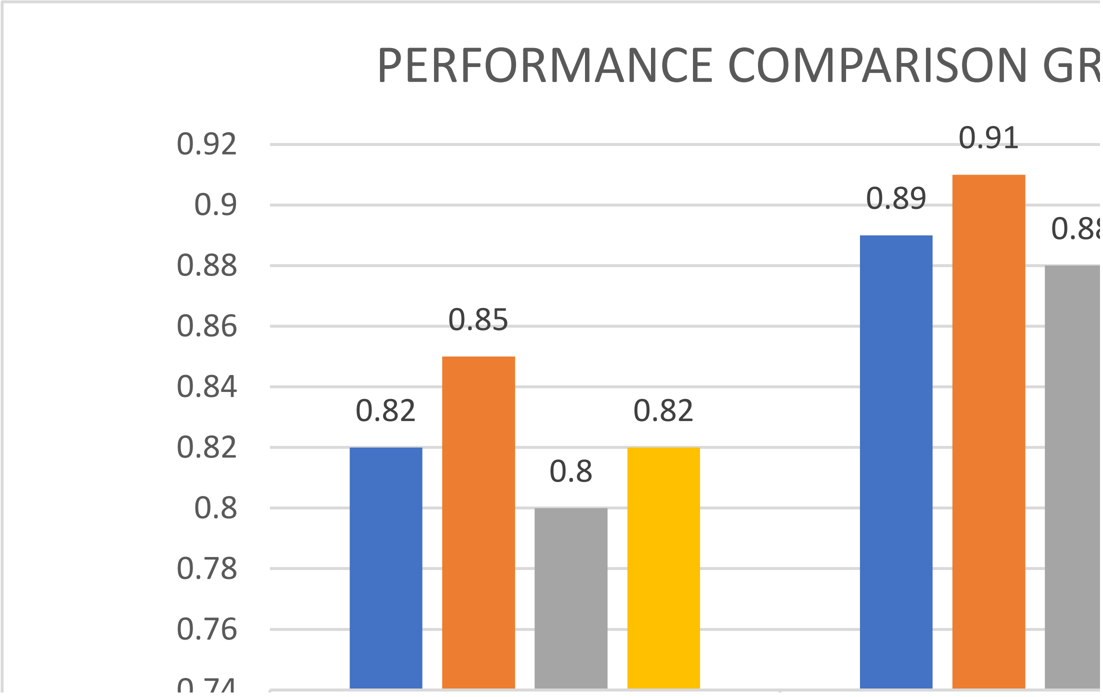

Fig 10. The importance of using the right model for stress detection tasks was emphasized

The importance of using the right model for stress detection tasks was emphasized in the discussion of the findings. Cat Boost has been shown to be more accurate and reliable than ANN in categorizing stress levels, despite ANN being a strong and commonly used model. The research demonstrated the promise of Cat Boost for real-world stress detection applications and its ability to use categorical characteristics.

This study's results show that the Cat Boost algorithm is superior to the artificial neural network (ANN) in detecting psychological stress; hence the study makes a contribution to the area. According to the results of the research, using Cat Boost to increase stress detection systems' accuracy and overall performance is a viable option. More advanced stress detection models may result from more investigation into ensemble approaches that combine the benefits of ANN and Cat Boost.

Cat Boost's interpretability and explainability of its decision-making process warrants more study to better understand the underlying processes leading to stress detection and inform mental health specialists. The paper's findings show Cat Boost's superiority in detecting psychological stress, opening the door to improved stress detection systems that may aid people in taking charge of their own health and wellness and facilitate the early intervention of mental health disorders.

5. Conclusion:

The purpose of this article was to use Artificial Neural Networks (ANNs) and the Cat Boost algorithm to compare different approaches to the identification of mental stress. Insights into the models' efficacy and potential in stress detection were gained via the study's in-depth research of their performance. In terms of identifying mental health issues, both the ANN and Cat Boost models performed well in head-to-head comparisons. Cat Boost, on the other hand, consistently outperformed ANN in all parameters including accuracy, precision, recall, and F1 score. This suggests that, in particular for datasets where category variables play a key role, Cat Boost is more appropriate for stress detection tasks. The algorithm's high performance may be attributed, in part, to its skill at dealing with such details.

The models' resilience and generalizability to fresh, unknown data was assured by their optimal training and fine-tuning. The danger of over fitting was reduced, and accurate assessments of the models' performance were obtained, thanks to cross-validation. The results of this study have real-world relevance for the improvement of stress detection systems. Cat Boost's high accuracy provides a potent tool for diagnosing and labeling different types of stress. The system's tailored advice may be invaluable in helping people reduce stress and improve their health.

Researchers may want to look at ensemble approaches in the future to see if they can build even more accurate stress detection models by combining the benefits of ANN and Cat Boost. Cat Boost's decision-making process may be investigated for its interpretability and explainability, which can provide important insights into the mechanisms affecting stress detection. The overall contribution of this study is to show how Cat Boost excels over ANN for detecting psychological stress. The results demonstrate the potential of Cat Boost in constructing accurate and dependable stress detection systems that may aid people in managing stress and increasing mental well-being, highlighting the significance of choosing suitable algorithms for stress detection tasks.

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Author contributions

All authors are equally contributed in preparing, experimenting and reviewing the article.

Conflicts of interest

The authors declare no conflicts of interest.

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