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ABSTRACT

Social media has grown immensely popular as a platform to communicate and interact with peers. It has played a crucial role in shaping modern-day dynamics and cultural trends. Social media, even though it has its benefits, it also has bad effects. It is being linked to depression nowadays as the usage of social media in excess has been deeply integrated into one's daily life. In this research paper, we aim to find out the important relationship between the use of social media and depression levels. We have used several machine learning algorithms to predict depression levels in social media users. Our dataset includes behavioral data, social media patterns, and demographic data. We have employed 5 machine learning algorithms, Out of which CatBoost stands out as the highest performer since it can accurately classify instances and predict depression levels based on the given attributes. We have introduced a stacking model as part of our contribution, it is particularly noteworthy because of how well it predicts depression levels. It uses CatBoost as the meta-classifier and the other four algorithms as base classifiers. We have also employed the decision tree methodology to find out the key features affecting the level of depression.

INTRODUCTION

Today's world is highly interconnected, especially digitally. Social media has become an integral part of our daily lives, serving not only as a platform for connection but also for expression. It is used for a myriad of purposes including speaking our thoughts, connecting with close friends and family, and expressing our personal identities. While social media undoubtedly offers numerous benefits such as enhanced communication and access to information, its impact on daily life, particularly on mental health, cannot be ignored. The primary focus of this study is to explore the connection between social media usage and the mental wellness of its users, utilizing various machine learning algorithms to predict levels of depression among them.

The influence of social media on mental health is profound. This is mainly because users are exposed only to a selective portion of others' lives online, which is carefully curated and often idealized. This virtual showcase can lead people into a loop of unhealthy comparisons. For instance, viewing images of friends enjoying seemingly perfect vacations or celebrating major life events can trigger feelings of inadequacy and discontent among those who perceive their own lives as less fulfilling.

Furthermore, the proliferation of social comparison and envy is a longstanding issue. Users often find themselves inadvertently comparing their own achievements, appearances, and lifestyles with those of others in their online circles. This non-stop exposure to seemingly idealized lives can provoke feelings of jealousy and dissatisfaction, potentially contributing to the onset or exacerbation of depressive symptoms.

The phenomenon of "Fear of Missing Out" (FOMO) further intensifies the impact of social media on mental health. Users may feel compelled to keep pace with the constant flow of updates, activities, and shared experiences, fostering a fear of missing out on social gatherings or opportunities. This can lead to feelings of isolation and loneliness, which in turn negatively impact mental health.

Our study uses a comprehensive dataset that includes various factors such as demographic features like age and occupation, along with social media dependency-related and behavioral questions. By integrating this diverse set of variables, we aim to capture holistic data that reflects the complex relationship between social media engagement, gender, and mental health.

In our research, we employed several advanced machine learning algorithms, testing five different models to understand their efficacy in predicting depression levels among social media users. Through rigorous analysis, we identified CatBoost as the most effective algorithm for this purpose. We implemented a stacking model using CatBoost as a meta-classifier, which demonstrated exceptional accuracy in our predictive tasks. Moreover, our research goes beyond mere prediction; it also helps identify the key features that affect depression levels, thereby offering deeper insights into the factors that contribute to mental health challenges among social media users.

To ensure the robustness of our findings, we conducted numerous tests to validate the reliability and validity of our predictive model. These included cross-validation techniques to avoid overfitting, as well as various performance metrics such as precision, recall, and F1-score to evaluate the effectiveness of our model comprehensively.

The implications of our study are significant. They suggest that interventions aimed at reducing the negative effects of social media on mental health should focus on mitigating the factors that lead to depression, such as the intensity of social comparison and the feeling of missing out. This could be achieved through educational programs that encourage healthier social media usage patterns and promote awareness of its potential psychological impacts.

In conclusion, our research provides valuable insights into the multifaceted ways in which social media influences individuals' mental health. By leveraging advanced machine learning techniques, we have not only identified critical factors contributing to mental health issues but have also taken a significant step towards understanding how to mitigate these effects. The findings of this study have important implications for both users and policymakers in crafting strategies that enhance the benefits of social media while minimizing its psychological risks.

LITERATURE REVIEW

In recent years, the influence of social media on mental health has garnered significant attention as digital platforms become increasingly integrated into daily life. The pervasive nature of social media usage has raised concerns about its potential implications for mental well-being, particularly regarding depression. While social media offers numerous benefits, such as facilitating communication and information sharing, research suggests that excessive usage may contribute to negative psychological outcomes.

Empirical studies have identified several mechanisms through which social media usage can impact mental health, with depression emerging as a prominent concern. Social comparison, characterized by individuals comparing themselves unfavorably to others based on curated representations on social media, can lead to feelings of inadequacy and dissatisfaction. Moreover, the perpetuation of unrealistic expectations and the pervasive fear of missing out on experiences portrayed on social media platforms can exacerbate feelings of loneliness and isolation, ultimately contributing to depressive symptoms.

To gain a deeper understanding of the complex relationship between social media engagement and mental health outcomes, researchers have turned to advanced computational techniques, notably machine learning. Machine learning algorithms offer a powerful tool for analyzing large datasets and identifying patterns that may elucidate the underlying mechanisms driving depressive symptoms among social media users.

A variety of machine learning algorithms have been employed in this domain, each offering unique strengths and capabilities in predicting mental health patterns based on social media data. Algorithms such as Random Forest, Decision Tree, CatBoost, Gradient Boost, and Extra Trees have been extensively explored for their efficacy in uncovering subtle correlations and predicting mental health outcomes with high accuracy.

Feature extraction plays a crucial role in identifying the most influential factors affecting mental health outcomes. By isolating key variables such as demographic characteristics, social media behavior patterns, and frequency of usage, researchers can gain valuable insights into the predictors of depressive symptoms among social media users.

Furthermore, the development of stacked models represents a promising advancement in predictive modeling for mental health outcomes. Stacked models integrate multiple machine learning algorithms, leveraging the strengths of each to enhance prediction accuracy and robustness. By combining algorithms such as CatBoost as a meta-classifier and others as base classifiers, stacked models offer a comprehensive approach to understanding the intricate relationship between social media engagement and mental health.

However, the ethical considerations surrounding the collection and analysis of social media data for mental health research cannot be overlooked. It is imperative to prioritize privacy and consent, ensuring that individuals' rights are respected and protected throughout the research process.

In addition to the aforementioned points, it's crucial to delve into the nuances of user interaction with social media platforms. Understanding how individuals engage with content, interact with peers, and respond to various stimuli within these digital environments can offer profound insights into their mental health dynamics.

One aspect worth exploring further is the role of social media algorithms in shaping users' experiences and potentially influencing their mental well-being. Algorithms govern the content individuals see on their feeds, often prioritizing posts that elicit strong reactions or align with users' past interactions. This can create echo chambers, where individuals are exposed to content that reinforces their existing beliefs or preferences, but it can also lead to exposure to harmful or triggering content.

Moreover, the impact of cyberbullying and online harassment on mental health cannot be overstated. Social media platforms provide avenues for individuals to connect and communicate, but they also serve as arenas where harmful behaviors can manifest. Cyberbullying, trolling, and other forms of online harassment can have devastating effects on victims' mental health, contributing to feelings of anxiety, depression, and even suicidal ideation.

Furthermore, the evolving nature of social media platforms and their integration into various aspects of daily life warrant ongoing exploration. As new features are introduced and usage patterns evolve, the potential implications for mental health may shift as well. For example, the rise of ephemeral content on platforms like Snapchat and Instagram Stories introduces new dynamics of self-presentation and social interaction, which may influence users' well-being in distinct ways compared to traditional feed-based platforms.

Another area ripe for investigation is the intersection of social media usage with other factors known to influence mental health, such as socioeconomic status, cultural background, and pre-existing mental health conditions. Understanding how these intersecting factors shape individuals' experiences on social media and their susceptibility to mental health issues can inform more targeted interventions and support strategies.

Building on this, interventions tailored to mitigate the adverse effects of social media on mental health are critical. These could range from developing digital literacy programs that educate users about the risks of over-engagement to creating tools that help users manage their social media use more effectively. Health professionals and educators can play a significant role by integrating mental health considerations into their practices and curricula, ensuring that individuals are equipped to navigate the complexities of social media healthily.

Moreover, policymakers should consider enacting regulations that encourage more transparency and accountability from social media companies regarding their role in user mental health. Social media platforms could be encouraged or mandated to develop and share data-driven insights into how their services affect users, which can inform both public policy and product development to better support user well-being.

Finally, ongoing research should continue to address the longitudinal effects of social media usage on mental health, exploring not just immediate impacts but also how these platforms affect individuals over longer periods. This could involve tracking changes in mental health status over time and analyzing how shifts in social media usage patterns relate to these changes.

In conclusion, while machine learning and computational techniques offer valuable tools for understanding the relationship between social media engagement and mental health outcomes, a multidimensional approach is necessary to capture the full complexity of this phenomenon. By considering factors such as algorithmic influence, online harassment, evolving platform dynamics, and intersecting demographic variables, researchers can paint a more comprehensive picture of how social media impacts mental well-being. This holistic understanding is essential for developing effective interventions and support systems to promote healthy digital habits and mitigate negative mental health outcomes in the digital age.

METHODOLOGY

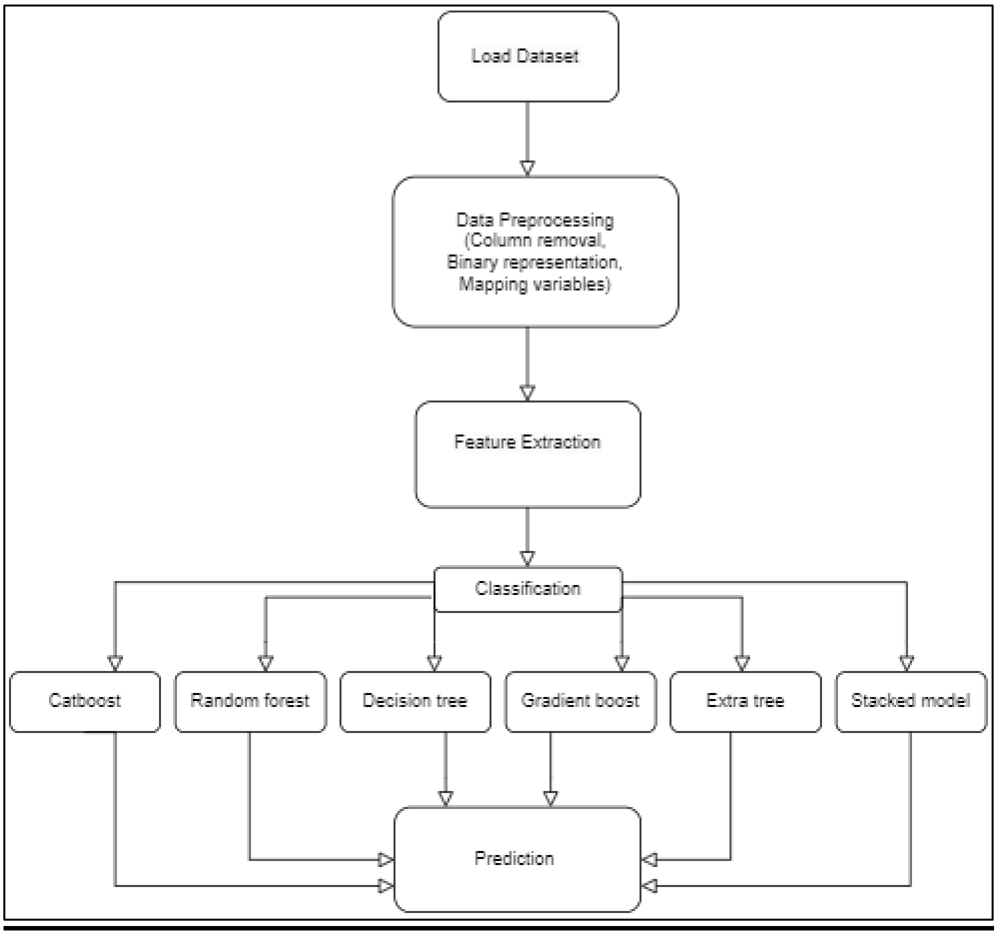

Fig 1. Workflow Diagram Of Proposed Methodology

I. Data Collection

In addition to the data obtained from Kaggle, we expanded the scope of our study by gathering information from our friends and families. This decision was motivated by a desire to enhance the breadth and depth of our analysis. By incorporating data from personal contacts, we were able to capture a wider range of perspectives and experiences, thus enriching our dataset. As a result, our dataset now comprises 2000 entries, providing valuable insights into the diverse ways in which individuals from varying backgrounds engage with social media and the potential implications for their mental health.

The inclusion of data from our direct contacts served to illuminate the research theme more authentically. By soliciting responses from individuals within our personal networks, we aimed to gain a more nuanced understanding of the connection between social media usage and mental health issues. This approach allowed us to delve deeper into participants' perceptions and experiences, thereby contributing to the ongoing discourse in this field.

Each participant's response to a set of 20 questions provided crucial insights into their social media habits and their perceptions of their mental well-being. By collecting such detailed information, we aimed to uncover patterns and trends that may elucidate the complex relationship between social media usage and mental health outcomes. Moreover, by supplementing traditional demographic data such as age and gender with qualitative responses from our personal contacts, we sought to provide a holistic and comprehensive analysis of the subject matter.

The questions designed for this study were carefully curated to include aspects of frequency and duration of social media usage, the types of platforms used, the content consumed and shared, and the emotional reactions to social media interactions. These questions also probed into the participants' self-perception and social comparisons initiated due to online interactions. With this detailed dataset, we are better equipped to identify key indicators of mental health stressors linked to social media use.

Furthermore, our analysis extends beyond simple statistical evaluations. We employed advanced analytical techniques, such as sentiment analysis and thematic coding, to interpret the qualitative data derived from open-ended responses. This blend of quantitative metrics and qualitative insights allows us to explore the subtleties of social media's impact on mental health, offering a richer narrative that quantitative data alone could not provide.

Additionally, engaging with our personal networks for data collection provided an ethical challenge that we navigated with careful consideration. Ensuring confidentiality and informed consent was paramount. We implemented rigorous data protection measures to safeguard the information provided by participants, ensuring that all data was anonymized and securely stored. This ethical rigor not only enhanced the credibility of our study but also reinforced the trust between the researchers and the participants.

Ultimately, the overarching goal of our study is to advance understanding of the link between social media use and mental health issues. By leveraging both quantitative and qualitative data sources, we aim to contribute meaningful insights to the existing body of research in this area. Our approach underscores the importance of considering diverse perspectives and experiences in order to gain a more comprehensive understanding of this complex and multifaceted phenomenon. The findings from this enriched dataset are expected to offer valuable contributions to policy-making, educational strategies, and public health interventions aimed at mitigating the negative impacts of social media on mental health.

II. Data Preprocessing

Data preprocessing is an essential phase in data analysis that involves cleaning and organizing data properly so that it is prepared for subsequent analytical procedures. This step is crucial because raw datasets might contain errors, inconsistencies, or missing values which could significantly affect the accuracy of the analysis. Without this important phase, the integrity of the entire analytical process could be compromised.

Furthermore, most machine learning algorithms predominantly work efficiently with numerical input. Therefore, transforming categorical variables into numerical formats is essential. This transformation should be carried out with consistency across all units and without introducing biases that could skew the results. Additionally, preprocessing can include feature scaling to normalize variable ranges. This process is vital as it speeds up algorithmic convergence and prevents any single factor from having an impact beyond its normal range due to scale differences.

Feature scaling methods like normalization or standardization adjust the data attributes to have a common scale without distorting differences in the ranges of values or losing information. Normalization typically adjusts the data measurements to fall between 0 and 1, whereas standardization transforms data to have zero mean and unit variance. These methods ensure that all input variables contribute equally to the analysis, enhancing the performance and accuracy of predictive models.

In conclusion, data preprocessing is a foundational step in the data science workflow, necessary for removing anomalies and standardizing inputs. This ultimately supports the development of more accurate and effective machine learning models.

A. Column Removal

In this initial phase of our data preprocessing, we meticulously remove undesired information such as timestamps and other irrelevant columns which do not contribute useful insights. This step is crucial as it helps in focusing the analysis on the most pertinent data, ensuring that our models are not misled by extraneous information. By eliminating these unnecessary elements, we reduce the noise in our dataset and increase the clarity and effectiveness of our subsequent analyses.

Furthermore, the process involves a careful examination of the data to identify and exclude records that may introduce bias. This bias could stem from redundant data points, outliers, or anomalies that skew the overall dataset. Trimming down the dataset in this manner not only streamlines the processing but also enhances the overall efficiency and reliability of the data.

As we refine the dataset, we also prepare it for further transformations such as normalization and encoding, which are essential for aligning the data into a format suitable for machine learning algorithms. Each step in this phase is performed with the utmost precision to ensure that the final dataset is optimized for accuracy and performance, laying a solid foundation for powerful insights and informed decision-making in later stages of the project.

B. Binary Representation for Social Media Platforms

Acknowledging the explicit nature of social media engagement, our data preprocessing method incorporates a binary representation technique. In this critical step, utilization patterns for each social media platform are meticulously encoded into binary columns. This transformation involves converting categorical data, such as the frequency of usage or type of interaction with each platform, into a series of binary (0 or 1) values. Each binary column corresponds to a specific aspect of user engagement, such as “active” or “inactive” status on a platform.

This binary encoding results in a more succinct and interpretable representation of data, making it easier for analysts and machine learning algorithms to process. The binary format streamlines the complexity of the data, reducing computational overhead and enhancing the efficiency of the analysis. It allows algorithms to quickly identify patterns and correlations that might not be evident in more complex data structures.

By adopting this approach, we ensure that our data is optimally prepared for effective evaluation. The binary representation not only facilitates a faster and more efficient analysis but also improves the accuracy of the predictive models developed from the data. This method is particularly beneficial in handling large datasets common in social media analytics, where speed and accuracy are crucial for timely and informed decision-making.

C. Mapping Categorical Variables

The subsequent step in our data preprocessing was the mapping of categorical variables. In our dataset, categorical variables such as gender and relationship status play a crucial role in understanding social media behaviors and their impact on users' mental health. However, to align these categorical variables with the technical requirements of machine learning models, we must convert them into numerical formats. This conversion is essential for maintaining uniformity across the data and for facilitating the algorithms' ability to process and analyze the information accurately.

Converting categorical values to numerical ones involves using techniques like one-hot encoding or label encoding. This transformation not only ensures uniformity but also helps in preventing algorithmic biases that can skew the analysis. Moreover, numerical representation significantly enhances the strength and quality of our machine-learning algorithms. It allows these algorithms to perform complex computations more effectively and to detect subtle patterns and correlations that might be missed with categorical data. The precise encoding of these variables is thus instrumental in increasing the predictive accuracy and reliability of our models, leading to more robust and insightful analytical outcomes.

By systematically transforming categorical variables into numerical data, we enhance the integrity and analytical capabilities of our dataset, enabling more effective evaluations and contributing to the deeper understanding of the intricate relationships between social media use and mental health.

The system meticulously divides the dataset into two distinct subsets for the training and testing phases. The dataset was randomly split in a 70:30 ratio, allocating 70% of the data for training with our machine learning model, while the remaining 30% was reserved for independent testing. This split was executed with utmost care to ensure that the training subset accurately represented the overall dataset, providing a comprehensive foundation for model training. Simultaneously, the testing subset was retained as an unbiased sample, crucial for evaluating the model’s performance.

During the training phase, we employed several innovative machine learning algorithms. This variety allowed us to explore different analytical approaches and optimize our model based on performance metrics. The choice of algorithms was guided by their suitability for handling the specific characteristics of our data, such as dimensionality and distribution. This strategic selection and rigorous training approach were designed to enhance the predictive accuracy and reliability of the model.

By conducting thorough training and testing, we aim to develop a robust machine learning model that reliably predicts outcomes, providing valuable insights into the complex dynamics captured in our data. This careful division and meticulous training strategy are pivotal in achieving a model that not only performs well on known data but also generalizes effectively to new, unseen data.

III.Feature Extraction

To enhance the effectiveness of support and interventions for individuals grappling with depression on social media platforms, it is imperative to gain insight into the factors that impact their mental well-being. Our study was designed with the primary objective of identifying these key factors through a comprehensive analysis of demographic characteristics and survey responses. By leveraging decision trees, we endeavored to elucidate the primary determinants influencing depression levels among users of social media platforms.

Decision trees served as a powerful analytical tool in our study, allowing us to systematically analyze a myriad of variables and their interrelationships. Through this approach, we were able to identify the most significant factors contributing to depression levels among social media users. This insight is invaluable in informing targeted support strategies and interventions aimed at mitigating the adverse effects of social media use on mental health.

Furthermore, our study underscores the importance of considering demographic characteristics alongside survey responses to gain a holistic understanding of the factors influencing depression levels. By examining a diverse range of variables, including age, gender, social media usage patterns, and perceptions of mental well-being, we were able to paint a comprehensive picture of the multifaceted nature of depression among social media users.

In summary, our study employed decision trees as a robust analytical framework to identify key factors influencing depression levels among individuals on social media platforms. By elucidating these factors, we aim to inform the development of targeted interventions and support strategies to better assist those struggling with depression in the digital age.

IV. Classification

We have used different machine learning techniques to identify different trends and to predict the levels of depression. A wide variety of approaches have been used here, each has its unique capabilities and this shows us the various ways social media influences mental health.This includes:

A. Random Forest Classifier

The Random Forest classifier is a powerful learning approach that has garnered significant attention in the field of machine learning. It combines multiple decision trees to enhance predictive performance significantly, making it a versatile and effective tool for various tasks. This ensemble method creates a diverse group of decision trees, each trained on random subsets of the training data and features. During prediction, the class with the most votes from the individual trees is chosen as the final output.

One of the key advantages of the Random Forest algorithm is its ability to handle high-dimensional data effectively. High-dimensional datasets pose challenges for many machine learning models due to the increased risk of overfitting and computational complexity. However, Random Forest mitigates these challenges by utilizing random subsets of features during training. This approach helps to decorrelate the individual trees and reduce the risk of overfitting, ensuring robust model performance and generalization to unseen data.

Moreover, Random Forest provides built-in feature importance measures, which is a valuable asset for understanding the underlying factors driving the model's predictions. By analyzing the importance of each feature, researchers and practitioners can gain insights into which predictors have the most significant impact on the model's output. This insight into feature importance can inform feature selection processes, allowing users to focus on the most influential predictors and potentially improve model performance.

Furthermore, Random Forest is known for its scalability and efficiency, making it suitable for handling large datasets with ease. The algorithm can parallelize the training process, leveraging multicore processors and distributed computing frameworks to expedite model training. This scalability is particularly advantageous in modern data environments, where datasets are often vast and computational resources are limited.

In summary, the Random Forest classifier stands out as a versatile and effective learning approach in the field of machine learning. Its ability to improve predictive performance, handle high-dimensional data, and provide valuable insights into feature importance makes it a popular choice for various applications. As machine learning continues to evolve, Random Forest remains a valuable tool for researchers, practitioners, and data scientists seeking robust and interpretable models for their datasets.

B. Decision Tree

The partitioning of the feature space into distinct regions is a fundamental aspect of the decision tree classifier, a cornerstone algorithm in machine learning. This process involves iteratively splitting the dataset into subsets based on the values of different features. At each node of the decision tree, the most informative feature is selected to partition the data, leading to the creation of distinct regions within the feature space.

This iterative splitting process continues until a stopping requirement is met, such as reaching a maximum depth or purity threshold. At this point, the decision tree is deemed complete, and each terminal node represents a distinct region within the feature space.

One of the key advantages of decision trees is their ability to provide insights into the dataset and highlight the importance of different features. By examining the structure of the decision tree, researchers can gain a deeper understanding of how various features contribute to the classification of data points. This insight can be invaluable in identifying the most influential predictors and understanding the underlying patterns within the dataset.

Moreover, decision trees offer interpretability, which is essential for understanding the model's behavior and communicating findings to stakeholders. Unlike some complex black-box models, decision trees provide a clear and intuitive representation of the decision-making process. Each branch of the tree represents a decision based on a feature value, leading to a transparent understanding of how input variables influence the model's output.

Furthermore, decision trees can handle both numerical and categorical data, making them versatile for a wide range of datasets. They are also robust to outliers and missing values, as the splitting process is based on relative comparisons rather than absolute values.

In addition to their interpretability and versatility, decision trees can be part of ensemble methods, such as Random Forests and Gradient Boosting Machines, which further enhance their predictive power. Ensemble methods combine multiple decision trees to improve generalization and reduce overfitting, resulting in more robust models.

Despite their strengths, decision trees have limitations. They can be prone to overfitting, especially when the tree is allowed to grow too deep or when the dataset is small. Regularization techniques, such as pruning, can mitigate overfitting by simplifying the tree structure.

In summary, decision trees are powerful tools for partitioning the feature space and providing insights into datasets. Their interpretability, versatility, and potential for ensemble learning make them valuable assets in the machine learning toolbox. However, researchers and practitioners must be mindful of their limitations and employ appropriate techniques to ensure optimal performance.

C. Gradient Boosting

The Gradient Boosting Classifier is hailed as an exceptionally powerful ensemble learning method in the realm of machine learning, revered for its ability to yield remarkable predictive accuracy and robustness. Operating on the principle of iteratively constructing decision trees, this method sequentially corrects errors made by preceding trees, thereby optimizing a differentiable loss function. By adding weak learners in a stage-wise manner, the algorithm effectively minimizes the gradient of the loss function, facilitating the creation of increasingly refined predictive models.

One of the defining strengths of Gradient Boosting models lies in their robustness and adeptness at handling complex datasets. Through the amalgamation of individual trees' collective strengths, Gradient Boosting models exhibit a remarkable capacity for capturing intricate patterns and relationships within the data. This depth of analysis often translates to superior predictive accuracy, enabling the model to make more precise predictions on unseen data.

Moreover, Gradient Boosting models offer several additional advantages that contribute to their widespread adoption and utility in various domains. One such advantage is their flexibility in handling different types of data, including numerical, categorical, and ordinal variables. This versatility allows Gradient Boosting models to seamlessly accommodate diverse datasets, regardless of their inherent complexities or structural nuances.

Additionally, Gradient Boosting models excel in capturing nonlinear relationships within the data, thereby enabling them to model complex phenomena with high fidelity. This nonlinear modeling capability is particularly valuable in domains where relationships between variables are not linear and may exhibit intricate interactions and dependencies.

Furthermore, Gradient Boosting models are renowned for their resilience against overfitting, a common pitfall encountered in many machine learning algorithms. Overfitting occurs when a model learns to capture noise or irrelevant patterns in the training data, leading to suboptimal generalization performance on unseen data. However, Gradient Boosting's iterative approach to model building, coupled with techniques such as regularization and shrinkage, helps mitigate the risk of overfitting, ensuring that the model generalizes well to new data instances.

In summary, the Gradient Boosting Classifier stands as a highly effective and versatile approach in ensemble learning, offering a potent combination of predictive accuracy, robustness, and flexibility. By iteratively refining predictive models and harnessing the collective strength of individual trees, Gradient Boosting models emerge as formidable tools in data analysis and predictive modeling tasks. As machine learning continues to advance, Gradient Boosting remains a cornerstone method, driving insights and discoveries across diverse domains and applications.

D. CatBoost

The CatBoost Classifier stands out as an exceptional gradient boosting library meticulously crafted to excel in the nuanced handling of categorical features within datasets. Unlike conventional approaches, CatBoost sets itself apart by leveraging an optimized implementation of gradient boosting, coupled with a sophisticated computation strategy and novel algorithms specifically tailored for feature discretization.

A prominent hallmark of CatBoost is its innate capability to effortlessly handle categorical variables, obviating the need for extensive preprocessing or hyperparameter tuning. This intrinsic feature not only streamlines the modeling process but also fortifies the model's resilience against overfitting, a common concern when dealing with categorical data.

Furthermore, CatBoost demonstrates exceptional performance, particularly in scenarios where datasets boast high-cardinality categorical features. Its advanced algorithms and efficient computation strategy empower it to navigate through complex data structures adeptly, thereby culminating in superior predictive accuracy and reliability.

At the heart of CatBoost's efficacy lies its robust and efficient handling of categorical features. Traditional machine learning algorithms often struggle with categorical variables due to their discrete and unordered nature. However, CatBoost employs innovative techniques to encode and utilize categorical information optimally, ensuring that valuable insights inherent in such features are fully captured and leveraged during model training and inference.

Moreover, CatBoost's adeptness in automatically handling categorical variables significantly alleviates the burden of manual preprocessing, thereby expediting the model development pipeline and enhancing productivity. Data scientists and machine learning practitioners can allocate their time and resources more efficiently, focusing on other aspects of the modeling process or exploring additional avenues for improving model performance.

Additionally, CatBoost's resilience against overfitting underscores its reliability and robustness in real-world applications. Overfitting occurs when a model learns to capture noise or spurious patterns in the training data, resulting in poor generalization to unseen data.

By incorporating mechanisms to mitigate overfitting, such as regularization techniques and built-in cross-validation, CatBoost ensures that the model's predictions remain accurate and dependable even in the face of noisy or complex datasets.

In summary, the CatBoost Classifier epitomizes a cutting-edge solution for gradient boosting, offering unparalleled capabilities in handling categorical features, fortitude against overfitting, and exceptional performance across diverse data scenarios. Its innovative approach and superior performance make it an indispensable asset in the toolkit of data scientists and machine learning practitioners, empowering them to tackle complex modeling challenges with confidence and efficacy.

E. Extra Tree

The Extra Tree Classifier, also known as Extremely Randomised Trees, emerges as a formidable ensemble learning method closely related to Random Forests yet distinguished by its unique approach. Similar to Random Forests, the Extra Tree Classifier constructs multiple decision trees; however, it introduces an intriguing twist: additional randomness injected during tree construction by selecting the best split among randomly generated ones.

This infusion of extra randomness serves as a potent tool in reducing variance and elevating the model's generalization prowess, thereby rendering Extra Trees less prone to overfitting compared to their counterparts. This advantage is particularly crucial in the realm of machine learning, where overfitting poses a significant challenge, impairing models' ability to generalize well to unseen data.

Moreover, the computational efficiency and scalability of Extra Trees render them invaluable assets in various machine learning tasks, especially those involving high-dimensional data. Their ability to handle large datasets with ease and efficiency makes them a preferred choice for practitioners and researchers alike seeking robust solutions for complex modeling challenges.

By harnessing the power of Extra Trees, researchers can delve into the intricate dynamics of predicting and understanding levels of depression among social media users with unparalleled depth and precision. The robustness and efficiency of Extra Trees empower researchers to navigate through complex datasets seamlessly, unveiling subtle patterns and relationships that may underlie depressive symptoms in social media users.

Furthermore, the versatility of Extra Trees extends beyond their application in depression prediction to a myriad of other domains and tasks. From sentiment analysis and customer churn prediction to fraud detection and recommendation systems, Extra Trees offer a versatile and effective solution for a wide array of machine learning problems.

In conclusion, the Extra Tree Classifier stands as a formidable ensemble learning method that complements and enhances the capabilities of traditional Random Forests. Its introduction of additional randomness during tree construction confers it with superior generalization ability and resilience against overfitting, making it a preferred choice for tackling complex machine learning tasks. Leveraging the power of Extra Trees, researchers can unravel the intricate relationships and patterns underlying diverse phenomena, including the manifestation of depressive symptoms among social media users.

V.Stacked Model

The introduction of the stacked model stands as a groundbreaking contribution to our research paper, designed to elevate the reliability and predictive accuracy of our model to unprecedented levels. This innovative approach, while relatively nascent in its inception, harnesses cutting-edge technology by amalgamating predictions from a diverse array of models, including Decision Tree, Random Forest, Extra Tree, Gradient Boost, and CatBoost.

At the core of the stacked model lies its remarkable ability to mitigate errors stemming from overfitting and noise through the aggregation of predictions from multiple models. By amalgamating the strengths of different algorithms, the stacked model offers a synergistic effect that transcends the capabilities of individual models, imbuing our predictions with enhanced robustness and stability.

Furthermore, the stacked model's intrinsic capability to decipher complex patterns within the dataset unlocks a new realm of possibilities for comprehensive data analysis. This unparalleled capacity facilitates a deeper dive into the intricacies of the data, empowering researchers to unearth subtle insights and uncover latent relationships that may elude detection when relying solely on individual models.

Moreover, the inherent flexibility of the stacked model underscores its adaptability to the unique characteristics of our dataset and modeling objectives. This dynamic nature enables seamless customization and optimization of the model, tailoring its architecture to address the specific challenges and complexities inherent in our data landscape.

By integrating this avant-garde approach into our research methodology, we underscore our steadfast commitment to rigorous methods and our relentless pursuit of cutting-edge ensemble learning techniques. Embracing the stacked model heralds a paradigm shift in predictive modeling, propelling us towards the forefront of innovation and positioning us to unravel the intricate tapestry of complex data relationships with unparalleled precision and insight.

In essence, the introduction of the stacked model heralds a new era of predictive modeling, characterized by heightened accuracy, unparalleled reliability, and unparalleled depth of insight. As we embark on this transformative journey, we are poised to redefine the boundaries of predictive analytics and unlock new avenues for knowledge discovery and scientific advancement. Through the adoption of the stacked model, we chart a course towards a future where data-driven insights serve as the cornerstone of informed decision-making and transformative change.

VI.Prediction Using Classifiers

In our study, we employed a diverse array of machine learning classifiers, including Decision Tree, Random Forest, Extra Tree, Gradient Boost, and CatBoost, alongside the innovative addition of the stacked model. This comprehensive approach allowed us to predict the levels of depression among individuals using social media platforms with increased accuracy and reliability.

Through our predictive analysis, we segmented the levels of depression into five distinct stages, namely "not depressed," "initial stage of depression," "moderate stage of depression," "significant stage of depression," and "severe stage of depression." This categorization enabled us to gain valuable insights into users' mental health statuses, leveraging information derived from their social media usage patterns and other relevant factors.

By classifying depression levels into multiple stages, we were able to capture the nuanced complexities of mental health outcomes among social media users. This granular approach facilitated a more comprehensive understanding of the diverse range of experiences and challenges faced by individuals in relation to their mental well-being.

Moreover, our categorization framework provided researchers and practitioners with a practical tool for assessing and addressing the varying degrees of depression severity observed within social media communities. By identifying users' mental health statuses based on their online behaviors and interactions, our study contributed to the development of targeted interventions and support strategies aimed at promoting mental wellness in the digital age.

In summary, our utilization of multiple machine learning classifiers, coupled with the introduction of the stacked model, enabled us to predict depression levels among social media users and categorize them into distinct stages. This approach facilitated a deeper understanding of users' mental health statuses and provided valuable insights for informing future research and intervention efforts in the realm of digital mental health.

Classification Metrics

Following the training phase, each model underwent rigorous testing to evaluate its performance using well-established classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. This meticulous evaluation process provided valuable insights into the models' predictive capabilities and informed decision-making regarding their suitability for further analysis and deployment.

By assessing these key metrics, we gained a comprehensive understanding of each model's ability to correctly classify data points across multiple classes, including "not depressed," "initial stage of depression," "moderate stage of depression," "significant stage of depression," and "severe stage of depression." This nuanced evaluation allowed us to identify the strengths and weaknesses of each model and make informed decisions regarding their utility in predicting depression levels among social media users.

Accuracy, precision, recall, F1-score, and confusion matrix analysis are widely recognized as standard measures for evaluating classification models' performance. By employing these metrics, we were able to assess the models' overall effectiveness in making accurate predictions and gain insights into their performance across different classes of depression severity.

Overall, this comprehensive evaluation process served as a robust framework for assessing the models' performance and guiding subsequent analysis. By leveraging these established metrics, we ensured that our conclusions were based on thorough and objective assessments of the models' predictive capabilities, thereby enhancing the reliability and validity of our findings.

Precision:Precision is the ratio of true positive predictions to the total number of positive predictions made by the model. It measures the proportion of correctly identified positive cases among all cases predicted as positive.

$$\boxed{Precision = TP / (TP + FP)}$$

Recall: Recall, also known as sensitivity or true positive rate, is the ratio of true positive predictions to the total number of actual positive cases in the dataset. It measures the model's ability to correctly identify all positive cases.

$$\boxed{Recall = TP / (TP + FN)}$$

Accuracy: Accuracy is the ratio of correct predictions to the total number of predictions made by the model. It measures the overall correctness of the model's predictions.

$$\boxed{Accuracy = (TP + TN) / (TP + TN + FP + FN)}$$

Confusion Matrix: A confusion matrix is a table that summarises the performance of a classification model by comparing predicted class labels with true class labels. It consists of four elements: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

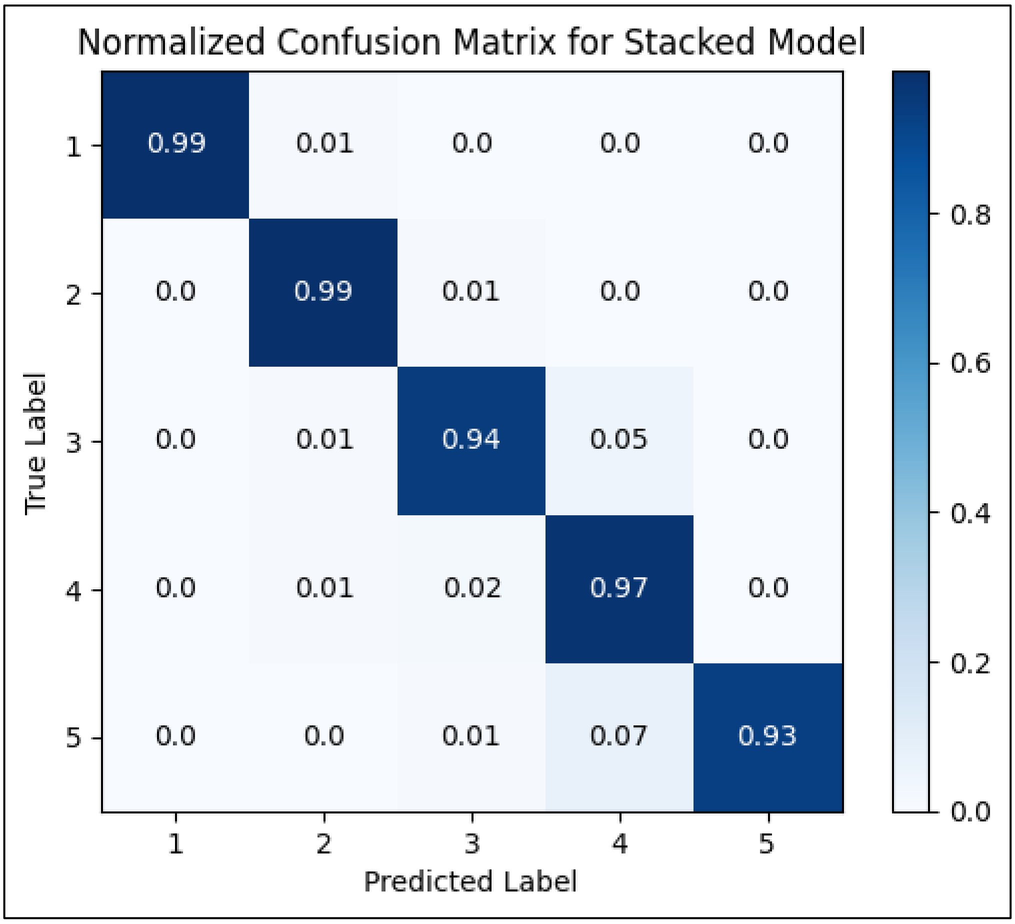

Fig 2. Confusion Matrix Of Stacked Methodology

F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a balanced measure of a model's performance, considering both precision and recall.

$$F1\ Score = 2 * (Precision * Recall) / (Precision + Recall)$$

Overall, this comprehensive evaluation process served as a robust framework for assessing the models' performance and guiding subsequent analysis. By leveraging these established metrics, we ensured that our conclusions were based on thorough and objective assessments of the models' predictive capabilities, thereby enhancing the reliability and validity of our findings.

Performance Analysis

The primary objective of this research was to assess the performance of various machine learning algorithms in real-world scenarios through detailed categorization tasks. Our findings revealed that the stacking model emerged as the top performer, achieving an exceptional accuracy of 96.16% along with precision, recall, and F1 scores all around 96%. This robust performance underscores the stacking model's effectiveness in accurately predicting outcomes across diverse datasets, making it a compelling choice for classification tasks prioritizing high accuracy.

CatBoost showcased outstanding performance, boasting an accuracy rate of 93.53% and consistently high precision, recall, and F1 scores, all hovering around 94%. This highlights CatBoost's proficiency in delivering precise predictions across a wide range of scenarios, further solidifying its status as a reliable classification algorithm.

Following closely behind, Random Forest demonstrated commendable performance with an accuracy of 91.34% and similarly high precision, recall, and F1 scores, all approximately 91%. Despite slightly lower metrics compared to CatBoost, Random Forest proved to be a robust algorithm capable of consistently accurate predictions across various contexts.

On the other hand, while Decision Tree exhibited a respectable accuracy of 88.27%, its precision, recall, and F1 scores did not match those of the top-performing algorithms. This suggests potential limitations in handling more complex classification tasks despite the algorithm's simplicity and interpretability.

Extra Trees performed decently with an accuracy of 86.07%, but its precision, recall, and F1 scores did not surpass those of the top performers. Similarly, Gradient Boost lagged behind with an accuracy of 74.01% and consistent but comparatively lower precision, recall, and F1 scores of 74%. These findings underscore the importance of selecting appropriate algorithms tailored to the dataset's properties and classification objectives to achieve optimal performance.

Algorithm	Accuracy	Precision	Recall	F1 Score
Decision Tree	88.27%	88%	88%	88%
Random Forest	91.34%	92%	91%	91%
Extra Tree	86.07%	86%	86%	86%
Gradient Boost	74.01%	74%	74%	74%
Catboost	93.53%	94%	94%	94%
Stacked Model	96.16%	96%	96%	96%

Table 1. Classification Metrics Of Machine Learning Classifiers

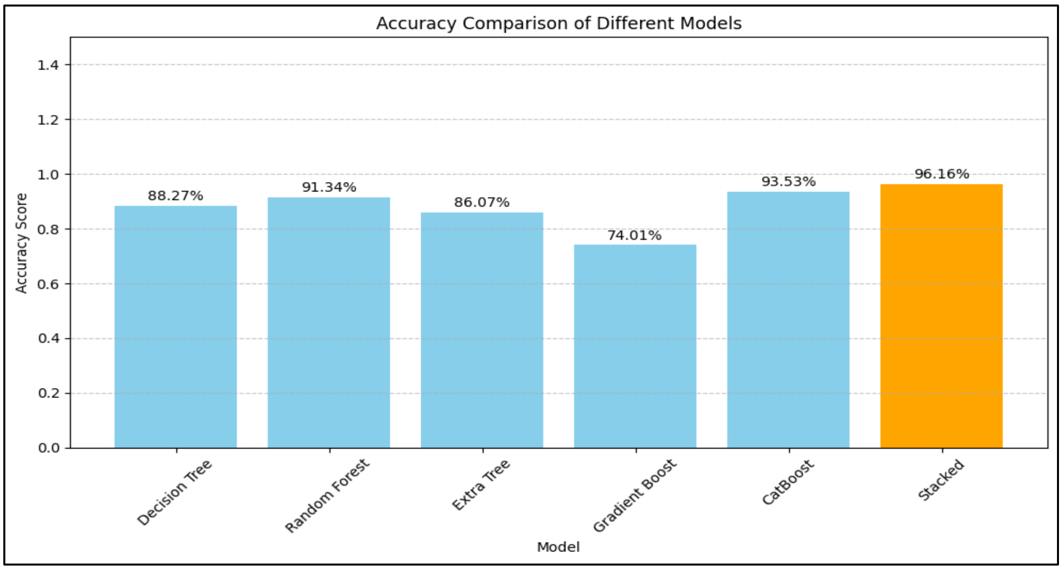

Fig 3. Bar Graph Showing Accuracy Comparisons Of Different Models

Algorithm	Accuracy	Precision	Recall	F1 Score
Decision Tree	88.27%	88%	88%	88%

Table 2. Classification Metrics Of Decision Tree

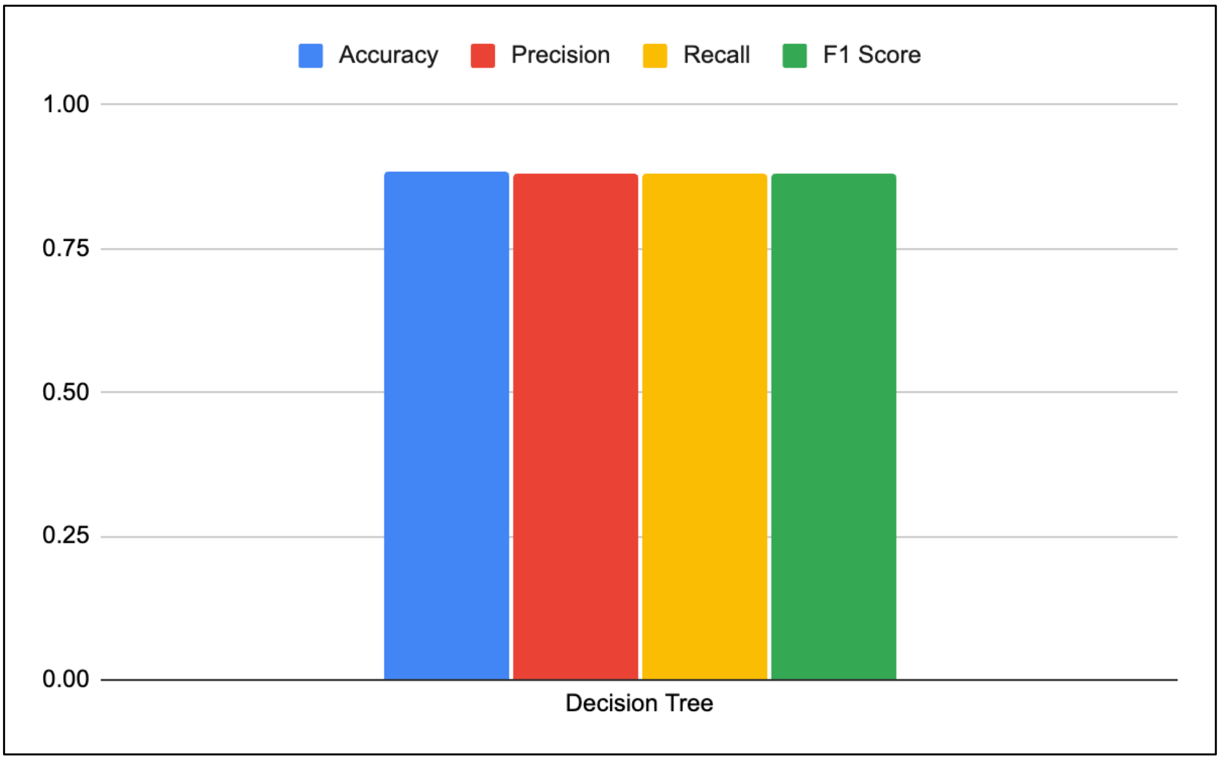

Figure 4. Bar Graph Showing Comparison of Classification Metrics Of Decision Tree

Algorithm	Accuracy	Precision	Recall	F1 Score
Random Forest	91.34%	92%	91%	91%

Table 3. Classification Metrics Of Random Forest

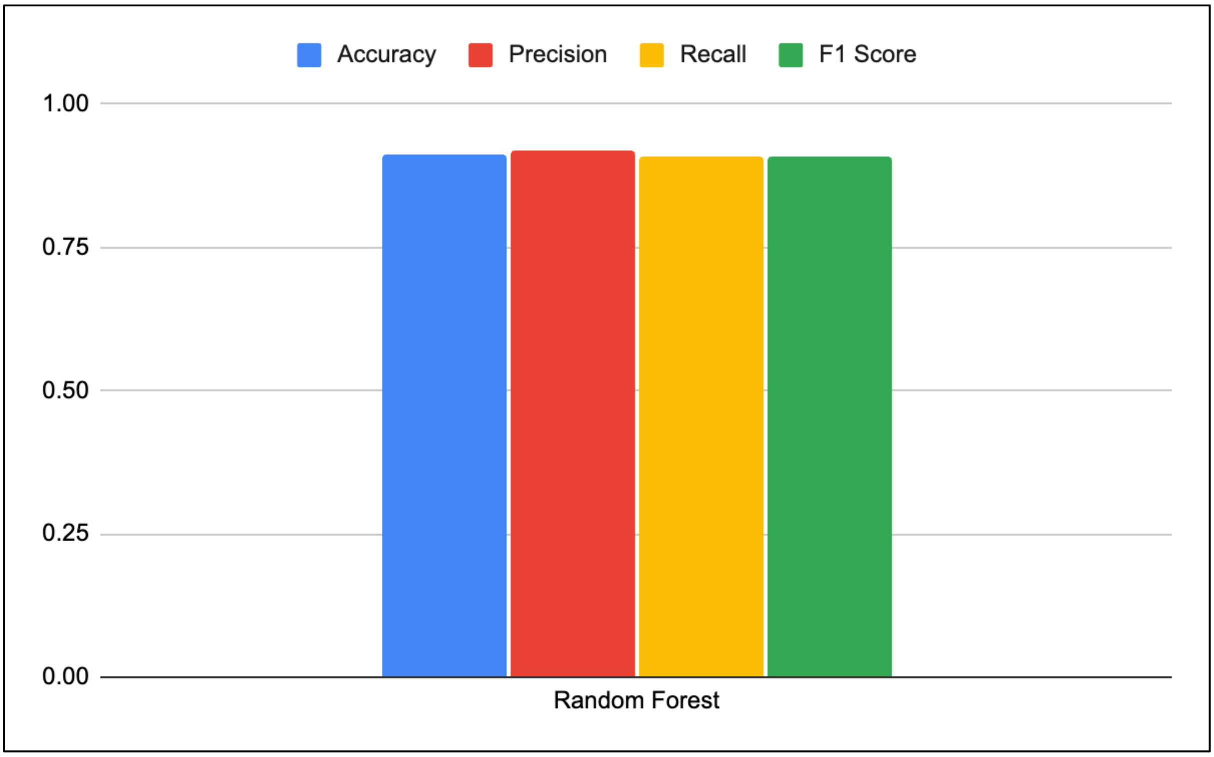

Figure 5. Bar Graph Showing Comparison of Classification Metrics Of Random Forest

Algorithm	Accuracy	Precision	Recall	F1 Score
Extra Tree	86.07%	86%	86%	86%

Table 4. Classification Metrics Of Extra Tree

Figure 6. Bar Graph Showing Comparison of Classification Metrics Of Extra Tree

Algorithm	Accuracy	Precision	Recall	F1 Score
Gradient Boost	74.01%	74%	74%	74%

Table 5. Classification Metrics Of Gradient Boost

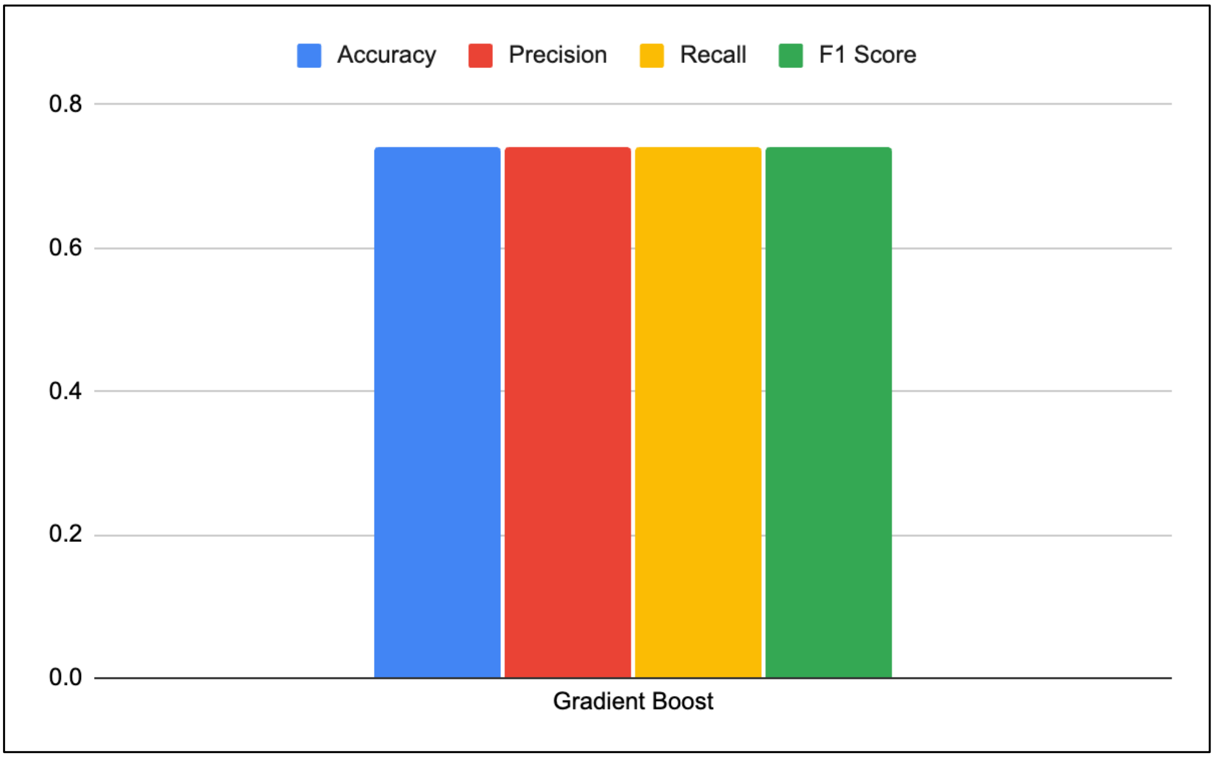

Figure 7. Bar Graph Showing Comparison of Classification Metrics Of Gradient Boost

Algorithm	Accuracy	Precision	Recall	F1 Score
Catboost	93.53%	94%	94%	94%

Table 6. Classification Metrics Of CatBoost

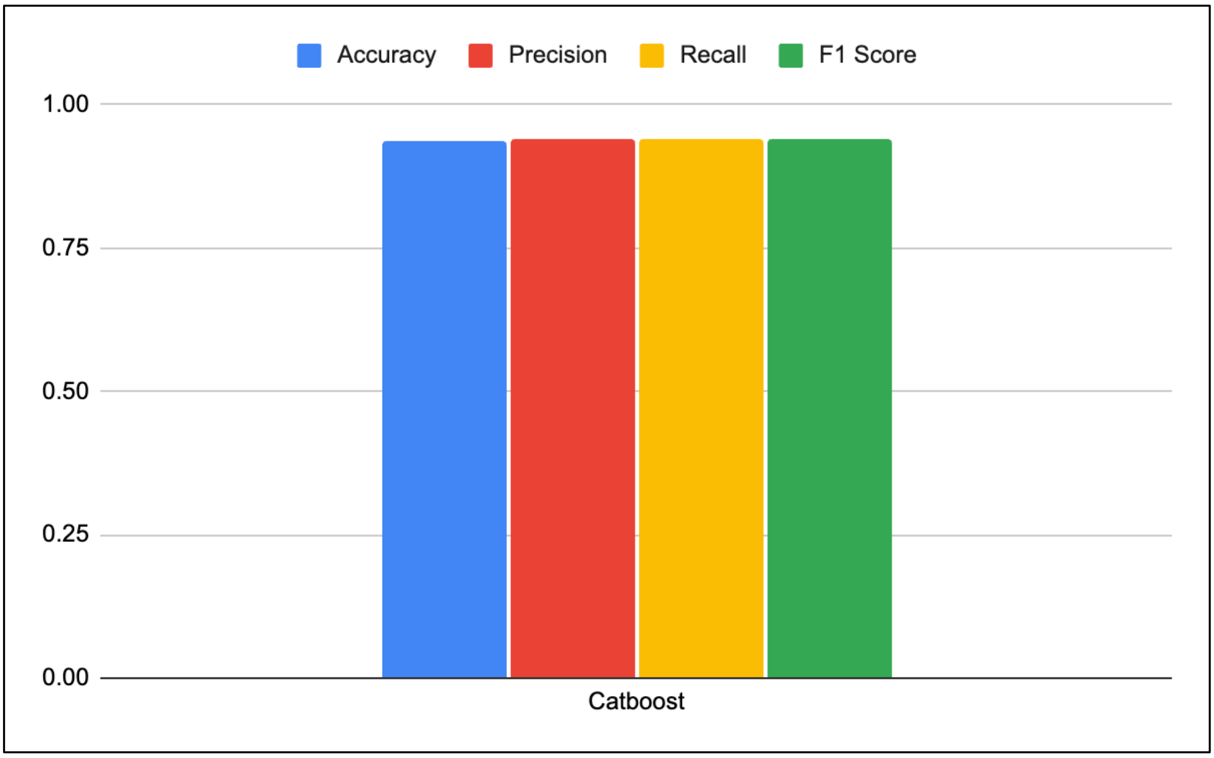

Figure 8. Bar Graph Showing Comparison of Classification Metrics Of CatBoost

Algorithm	Accuracy	Precision	Recall	F1 Score
Stacked Model	96.16%	96%	96%	96%

Table 7. Classification Metrics Of Stacked Model

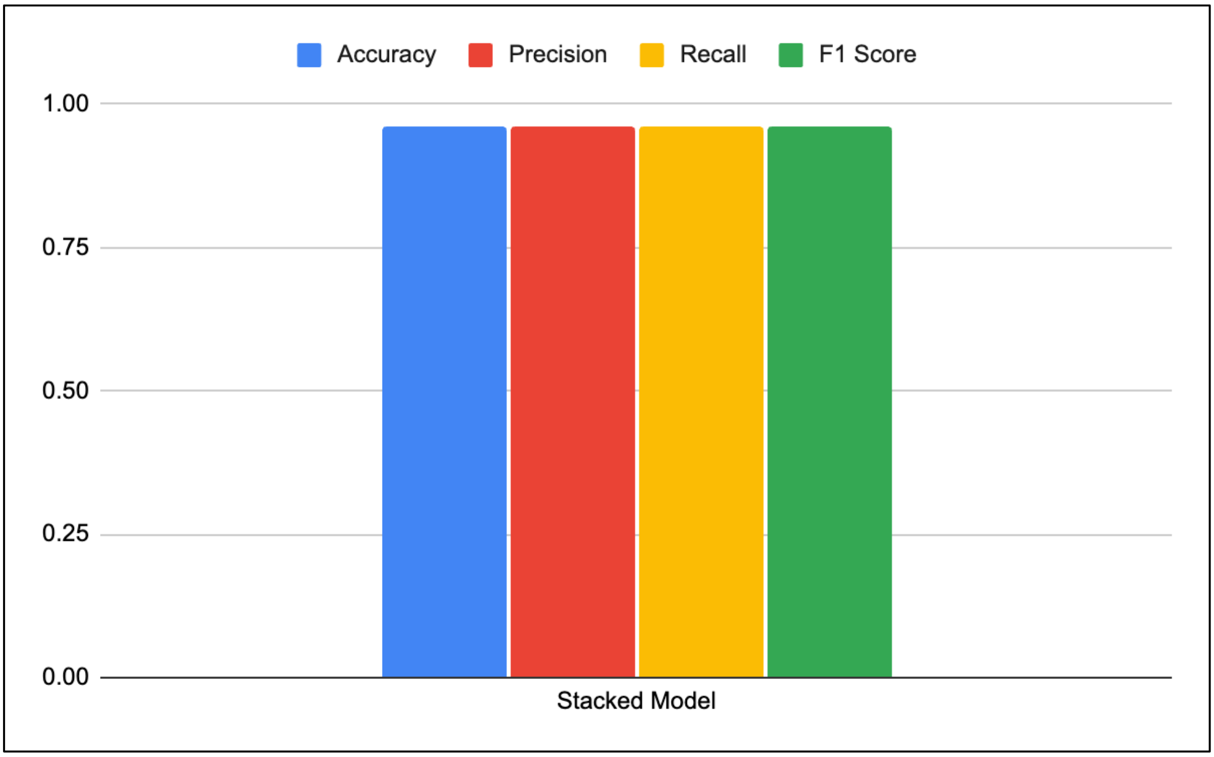

Figure 8. Bar Graph Showing Comparison of Classification Metrics Of Stacked Model

The research delves into the intricate relationship between an individual's feelings, behaviors, and levels of depression, shedding light on the diverse characteristics of these features. Notably, "Fluctuations in daily activities and interests" emerged as the top contributing factor, constituting approximately 24.64% of the top features. This underscores the profound impact of mood fluctuations on emotional well-being.

Social media-related factors also emerged as significant contributors, with "Seeking validation from social media features" accounting for 16.84% and "Getting distracted by social media" for 10.44% of importance among the top features. These findings highlight the complex interplay between mental health and social media engagement patterns.

Moreover, demographic features such as "Age" demonstrated significant importance, accounting for 19.39% of feature importance among the top features. This underscores the profound influence of age-related factors on an individual's susceptibility to depression symptoms.

The identification of these crucial features was made possible through the utilization of decision trees, a powerful analytical tool capable of uncovering complex relationships between variables. By employing this methodology, researchers were able to pinpoint key factors such as fluctuations in daily activities, social media engagement patterns, and demographic characteristics like age. This underscores the efficacy of machine learning methods in unraveling the multifaceted nature of depression and highlights the importance of data-driven approaches in mental health research and intervention.

In summary, the research findings suggest that a multitude of factors, including behavioral characteristics, social media engagement, and demographic features, significantly contribute to depression levels. This overview emphasizes the necessity of employing a comprehensive approach to assess mental health and recommend subsequent treatments, taking into account the intricate relations between individual characteristics and their environment.

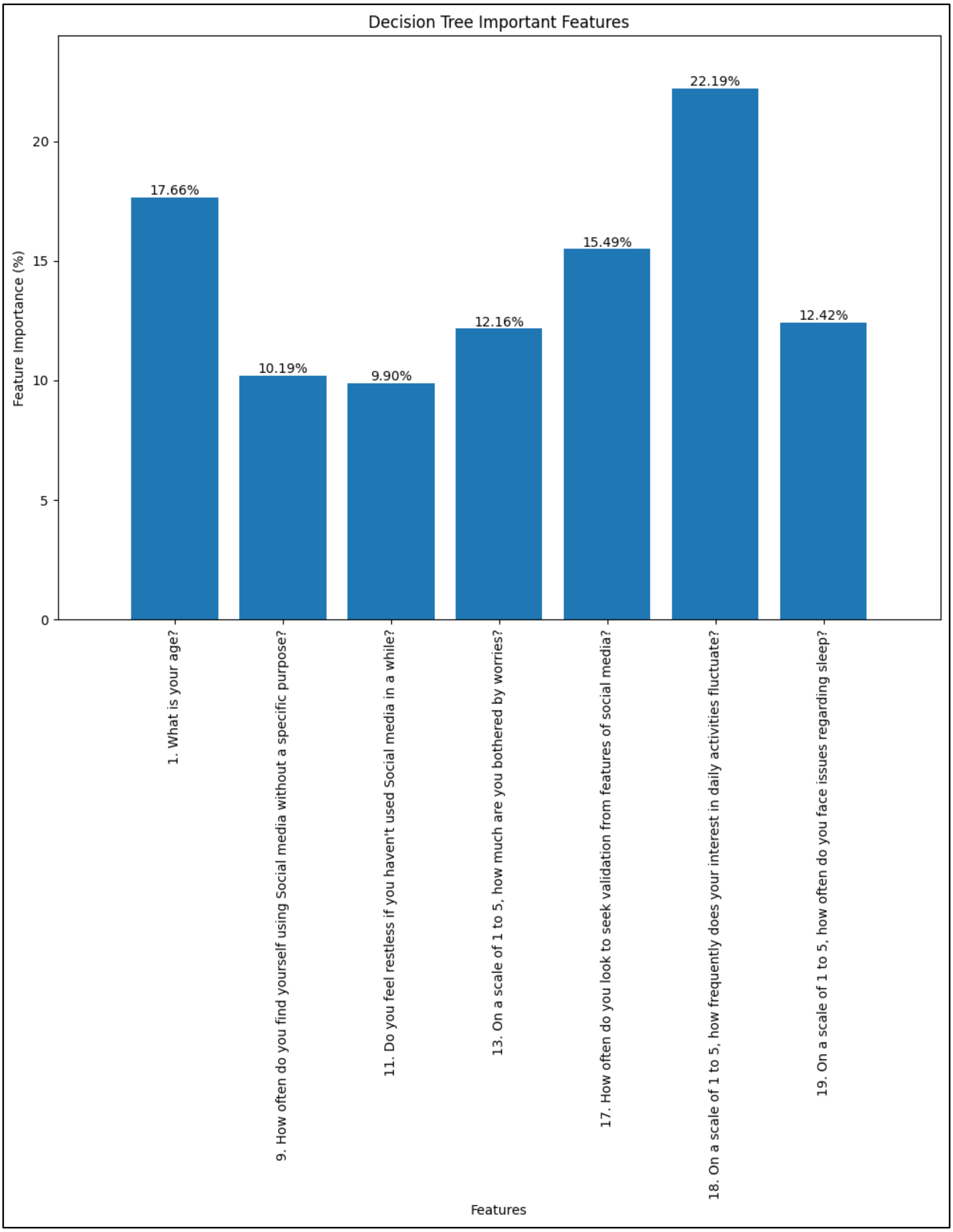

Figure 9. Bar Graph showing top 8 features affecting level of Depression

CONCLUSION

In our study investigating the correlation between social media usage and mental health, we took into consideration various factors such as age, gender, and social media habits. Employing a range of algorithms including Random Forest, Decision Tree, CatBoost, Gradient Boost, and Extra Trees, we aimed to comprehensively analyze the impact of social media on mental well-being. Our novel contribution was the introduction of a stacking model, which utilized CatBoost as the meta-classifier and the remaining four algorithms as base classifiers. Remarkably, the stacking model exhibited the highest accuracy, underscoring its efficacy in predicting depression levels based on the provided factors.

Furthermore, our study conducted a detailed decision tree analysis to identify key attributes associated with depression. We found that social media patterns, including purposeless usage and comparisons, significantly influenced mental well-being. Individuals experiencing challenges in attention concentration and sleep reported higher levels of depression. Consequently, addressing these aspects is deemed crucial for the effectiveness of mental health interventions.

Looking ahead, there are several innovative avenues for future research in the realm of social media and mental health. For instance, analyzing how social media usage evolves over time and its impact on individuals' mental well-being could provide valuable insights. Additionally, studying individuals' social media usage patterns and the content they engage with can offer further understanding of their mental health status.

Moreover, it is imperative to ensure ethical data collection practices, collaborate with domain experts, and advocate for evidence-based policies to promote better mental health outcomes. By adopting these strategies, future research endeavors can contribute to a deeper understanding of the complex interplay between social media and mental health and pave the way for more effective interventions and support mechanisms.

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Paper8

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