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Original Research Article

Predicting Mental Health Risk Using Machine Learning Based on Instagram Usage Patterns

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Abstract: The rapid growth of social media platforms has significantly changed the way people communicate, interact, and share information in modern society. Among these platforms, Instagram has become one of the most widely used social networking applications, especially among young adults and students. Although social media offers benefits such as communication, entertainment, and self-expression, excessive usage has also been associated with mental health issues including stress, anxiety, depression, loneliness, and low self-esteem. Early identification of such mental health risks is important to provide timely support and preventive care. This research proposes a machine learning-based approach to predict mental health risk using Instagram usage behaviour. Important behavioural features such as daily Instagram usage time, posting frequency, average likes per post, follower count, and night-time activity are analysed to identify potential risk patterns among users. Several machine learning classification algorithms including Logistic Regression, Decision Tree, Support Vector Machine (SVM), and Random Forest are implemented using the Scikit-learn library. The models are evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Experimental results show that the Random Forest classifier achieved the highest prediction accuracy compared to other models. The findings demonstrate that machine learning techniques combined with social media behavioural analysis can contribute to early mental health risk detection and support the development of intelligent preventive healthcare systems.

Keywords: Machine Learning, Mental Health Prediction, Instagram Usage Patterns, Random Forest, Social Media Analytics, Classification Algorithms.

1. Introduction

The rapid growth of social media platforms has changed how people interact, communicate, and consume information. Instagram has become one of the most widely used apps, especially among young adults and adolescents. While social media has many benefits for connection, self-expression, and sharing information, excessive and unregulated use has been linked to various mental health issues, including anxiety, depression, stress, and lower self-esteem. Early research mainly focused on the psychological effects of prolonged social media use. Studies found that users who spend long hours on platforms like Instagram or who often engage in social comparison tend to show signs of emotional distress and psychological vulnerability. These findings have sparked interest in using digital behavioural data as an indicator of mental health risk. With improvements in machine learning and data analytics, researchers have started to explore automated methods to detect and predict mental health risks based on observable online behaviours. Techniques that analyse text, image features, and usage patterns have shown promise in identifying individuals at risk of depression and other mental health conditions. This research proposes a machine learning-based system that looks at Instagram usage patterns to predict mental health risk. Important behaviour features like daily usage time, posting frequency, average likes per post, follower count, how often users check their screens, and night-time activity serve as input for classification models, including Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest. These models use the Scikit-learn library and are evaluated with standard metrics like accuracy, precision, recall, and F1-score. The goal of this study is to show how data-driven approaches can help identify mental health risks early, allowing for timely intervention and preventive care. The rest of this paper is organized as follows: Section 2 reviews related work; Section 3 provides technical background; Section 4 describes the system design and implementation; Section 5 covers the experimental methodology; Section 6 presents results and discussion; Sections 7 and 8 address limitations and conclusions, respectively.

2. Related Work

The link between social media use and mental health has become an important research topic in recent years. As platforms like Instagram became part of everyday life, researchers began to look at how online behaviour can affect emotional well-being. Early studies mainly focused on the psychological effects of social media. They reported that too much use could lead to anxiety, stress, depression, loneliness, and lower self-esteem [1]. Researchers found that users who spend long hours online or often compare themselves to others tend to show signs of emotional distress. These findings sparked interest in using digital activity as a potential indicator of mental health risk. Several researchers later used machine learning techniques to analyse social media data for predicting mental health [2]. Some studies examined captions, comments, and posts through text analysis, while others looked at measurable usage patterns like screen time, number of posts, likes, comments, and night-time activity. Algorithms such as Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest have classified users into different mental health risk levels. In many instances, these models achieved promising accuracy and showed that machine learning can help in early detection of mental health issues [3]. Recent research has also looked into deep learning models for detecting depression through social media data [4]. Methods such as neural networks and natural language processing, including transformer-based models like BERT [5], have improved prediction performance in some studies. However, these methods often require large datasets, significant computing power, and complicated implementation. For both academic research and practical use, simpler machine learning models may offer better comprehension and easier implementation while still producing reliable results. Although many studies have examined social media and mental health, few have focused specifically on Instagram usage patterns using simple classification models. Most studies combine data from multiple platforms or depend heavily on text-based analysis. There is still a need for research that assesses how Instagram activity alone can predict mental health risk [6]. This study addresses that gap by analysing Instagram usage patterns and comparing basic machine learning models to find an effective and practical prediction method.

3. Technical Background

3.1 Machine Learning for Mental Health Prediction

Machine learning can be defined as a field within artificial intelligence whereby computers are trained to learn and predict outcomes based on the patterns found within data, without being programmed explicitly to perform particular tasks [7]. Machine learning plays an essential role in this study where patterns and connections from Instagram users' online activity are analysed using machine learning algorithm to identify the potential mental illness patients among the population. Through machine learning, data can be analysed to identify hidden patterns and connections not noticed before through manual observations.

Features used for analysing include Instagram related such as daily time spent, number of posts, average likes received by the user, followers, and activities during the night. From these features, users whose patterns indicate that they are at a risk of having mental illness can be detected. People who spend too much time on social media, especially Instagram or even check frequently could have a higher mental health risk [1].

Some of the classification models used in this study include logistic regression, decision tree, support vector machine, and random forest. Classification models work by comparing user behavioural characteristics and assigning them to corresponding mental health risk categories.

3.2 Decision Tree Model

The Decision Tree classifier belongs to those supervised learning algorithms which are the most frequently applied for solving classification problems. This algorithm is based on the division of the entire dataset into several smaller subsets according to specific conditions. In the current project, the Decision Tree will use such variables as daily usage time, the number of posted images per week, likes per image, followers' quantity, and others related to user activity in order to determine the mental health risk level of individuals.

The decision tree consists of various nodes and branches. Each node corresponds to a particular condition connected with a specific feature of the dataset, while branches serve as directions to follow depending on the truth of the corresponding condition. The final node, or leaf node, gives the prediction. For instance, some nodes can be focused on the daily Instagram usage above/below a certain number of hours. Other nodes can refer to average likes, etc. The data set follows the selected path and gets a final output after reaching the leaf node.

The strength of the Decision Tree lies in its capacity to work with both numerical and categorical data without making any assumptions about the distribution of the data.

3.3 Overview of Proposed System

The proposed system is an approach designed to predict the risk of mental health problems based on the analysis of Instagram behaviour through the application of machine learning. The full process of constructing a system for predicting mental health risks starts from the collection of data about Instagram usage. The attributes considered significant include age, hours of usage per day, weekly posts, the number of likes per post, and followers' counts. The collected dataset is saved in the CSV and Excel formats to process further using the Python language. The preprocessing process involves improving the quality of the dataset. Missing values are found and deleted, as well as some unnecessary columns are excluded, such as user identification numbers. The chosen features are scaled down to ensure that they lie in the same range. Such actions positively affect the performance of machine learning methods and facilitate the work of predictive-models.

Then, the method of K-Means clustering is used to separate users into clusters based on their behaviour on Instagram. Clusters are translated into mental health categories such as Low Risk and High Risk. Then, labels of risk are assigned to clusters, and a dataset is split into training and testing subsets.

Table 1: Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	84%	84%	84%	83.2%
Decision Tree	99%	99%	99%	99%
SVM	89%	89%	89%	88%
Random Forest	99%	99%	99%	99%

3.4 Dataset Description

This research makes use of a synthetically generated dataset named Instagram Mental Health 2026, constructed for experimental and demonstration purposes, containing records of 500 simulated users. The dataset includes five input features namely Age, Daily Instagram Usage, Hours, Post Per Week, Average Likes Per Post, No of Followers. The target variable Mental Health Risk is divided into two categories — Low Risk with 363 users and High Risk with 137 users. The dataset was loaded in CSV format and pre-processed using the Pandas library in Python.

4. System Design and Implementation

This research employed the development of an automated machine learning system that can utilize Instagram user data to estimate mental health risks. The decision to use Python programming language to build the machine learning system is made based on its capability to create simple and powerful libraries for analysing datasets and applying machine learning algorithms [7]. In other words, Python allowed the researchers to concentrate only on those features that could help to predict the risk of developing psychological problems, such as Instagram usage duration, posting rate, number of likes, etc.

First of all, the dataset must be imported by means of Pandas library. Then, all unnecessary columns can be deleted and checking for any missing values in the imported data is conducted. Selected features can be normalized using the Standard Scaler function in order to ensure that all of them will be within the same value range. Further, K-Means Clustering algorithm will be applied to split the whole dataset and assign such risk labels as Low Risk and High Risk. They will be used during further supervised learning.

Then, different machine learning models like Decision Tree, Logistic Regression, Support Vector Machine, and Random Forest can be trained on the collected dataset.

4.1 Overall Architecture

In general, the design of the proposed system is to predict the risk of mental problems based on the analysis of data on user's activity on Instagram using machine learning techniques. As an initial step, data gathering is performed. In particular, the system uses data on age, time spent on Instagram on a daily basis, number of posts on a weekly basis, number of likes on a post, screen checks, number of followers, and night-time activity available from the Instagram dataset. Features mentioned above can be used to reflect online behaviour and might be used to assess the mental condition of users [1].

In the preprocessing stage, the quality of collected data is enhanced. At this stage, missing values are filled up. Additionally, unnecessary variables such as users' identification numbers are deleted from the data. The chosen features are standardized in order to normalize values to ensure machine learning models can work effectively without any errors resulting from different scales.

As the second main step of the architecture, risk identification is performed. It includes grouping the data using K-Means clustering techniques and labelling the created clusters as Low Risk or High-Risk clusters. Then, the dataset is split into two subsets : training and testing.

4.2 Model Implementation

The proposed system was implemented using Python and machine learning libraries [7]. First, the Instagram dataset was loaded from a CSV file with the Pandas library. After loading the data, we checked for missing values and removed unnecessary fields like user identification numbers. We selected important features such as age, daily Instagram usage hours, posts per week, average likes per post, and follower count as input variables for the prediction system. These features were then standardized to improve model performance.

After preprocessing, we applied K-Means clustering to group users into different mental health categories. The clusters were converted into risk labels like Low Risk and High Risk. We split the processed dataset into training and testing sets, with 80 percent used for training and 20 percent for testing. This setup allowed us to evaluate the model on new data.

The machine learning models used in this research included Decision Tree, Logistic Regression, Support Vector Machine, and Random Forest. Each model was trained on the training dataset and tested on the testing dataset. We compared the prediction results using accuracy, precision, recall, and F1-score. Finally, we performed a graphical comparison to identify the best model for predicting mental health risk based on Instagram usage patterns.

4.2.1 Support Vector Machine Algorithm

The Support Vector Machine model is implemented in Python using the Scikit-learn library to classify users into different mental health risk categories [7]. After preprocessing the dataset, selected Instagram usage features such as age, daily usage hours, number of posts, average likes per post, and follower count are used as input for the model. These features help the algorithm identify patterns that may indicate low or high mental health risk among Instagram users.

The SVM algorithm works by creating an optimal boundary between different classes so that the separation between risk groups becomes more accurate. During implementation, the model learns from the available user data and then predicts the mental health risk category for new users in the testing dataset. After prediction, the performance of the Support Vector Machine model is measured using evaluation metrics such as accuracy, precision, recall, and F1-score.

4.2.2 Logistic Regression Implementation

The Logistic Regression model was implemented using the Scikit-learn library to predict mental health risk based on Instagram usage pattern. We built it in Python with Scikit-learn to predict mental health risks based on how people use Instagram. First, the dataset was analysed and relevant behavioural features were selected for model training. These include age, how many hours someone spends on Instagram each day, their weekly post count, average likes per post, and follower number.

Once we had our features, the model learned from a training dataset. It studied how these patterns connect to mental health risks, essentially figuring out the chances that someone falls into a certain risk group. With Logistic Regression, it takes those user details and runs them through a function that outputs a probability value. If that number is high enough, the model flags the user as High Risk; if it's low, they go into the Low-Risk group.

4.3 Model Execution and Prediction Workflow

The prediction system takes five user-level attributes as input — age, daily time spent on Instagram, number of posts per week, average likes received per post, and total follower count. These attributes reflect the online behaviour of each user and form the foundation for mental health risk classification.

Before training begins, the dataset goes through a preparation stage. All input features are scaled to a common range using Standard Scaler. This step is necessary because certain algorithms, particularly Support Vector Machine, produce inconsistent results when input values differ significantly in magnitude. Once scaling is complete, the dataset is divided into two parts — 80 percent for training and 20 percent for testing.

One challenge with this dataset is that no mental health labels were available from the start. To address this, K-Means clustering was applied to the data. The algorithm grouped users into two distinct clusters based on their usage behaviour. These clusters were then manually interpreted and assigned as Low Risk and High-Risk categories. The resulting labels were used as target values during supervised model training, allowing the classification algorithms to learn patterns associated with each risk group.

4.4 Metrics Collection

To assess the performance of each machine learning model, four standard evaluation metrics were used: accuracy, precision, recall, and F1-score. These metrics together provide a complete picture of how well each model performed in identifying mental health risk categories.

Accuracy refers to the percentage of total predictions that the model got right. It gives a general idea of overall model performance across both risk categories.

Precision indicates how reliably the model identifies high-risk users. A higher precision value means the model is making fewer mistakes when flagging someone as high risk.

Recall measures how many of the actual high-risk users the model was able to correctly detect. A strong recall value means fewer high-risk individuals are being missed by the model.

The F1-score combines both precision and recall into a single value. It is especially useful in this study since the number of high-risk and low-risk users in the dataset is not equal.

All four metrics were calculated on the testing portion of the dataset, meaning the models were evaluated on data they had not seen during training. This approach ensures that the results reflect real predictive ability rather than memorisation of training data.

One important point to keep in mind is that the risk labels used in this study were not based on actual clinical diagnosis. They were generated through K-Means clustering, which means the models essentially learned to replicate the patterns created by the clustering algorithm. This factor was carefully considered while drawing conclusions from the results.

4.5 System Configuration

The system was developed using Python, along with other machine learning libraries. For handling data, Pandas was used for data loading and preprocessing. In order to visualize data, Matplotlib and Seaborn were used. On the other hand, we utilized Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest as models, implementing them with the help of Scikit-learn library. Data was normalized using Standard scaler before starting the training process. The application was successfully executed on a local system with all required libraries and dependencies installed.

5. Experimental Methodology

5.1 Variables

In our experiment, some independent variables are considered. These include the factors like age, Instagram usage hours per day, number of posts in a week, number of likes per post, and total followers. The output will be based on the mental health risk category, which will be divided into 'High Risk' and 'Low Risk' categories. Because we do not have labels from our data set, we apply K-Means clustering to categorize them. Further, there are several machine learning methods for comparison purposes, including Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest.

5.2 Procedure

In the procedure, the initial stage involves data preprocessing, whereby the irrelevant data such as user identification attributes are removed from the data. The selected features include age, hours spent on Instagram daily, number of posts made every week, average number of likes per post, and number of followers. Feature scaling is done on the features through standardization. For the data to be able to have the target values for training purposes, k-means clustering is performed to categorize the data into two classes, high-risk and low-risk users. The labels from the k-means clustering will serve as the target variables for training of the machine learning models. The labelled data were divided into training and testing subsets at a ratio of 80:20 respectively. Four machine learning models including logistic regression, decision tree, and support vector machine, and random forest were trained using the training subset. The four models learned the relationship between Instagram behavioural data and the target variables. The testing data were then used to predict target variables for the testing data set.

5.3 Metric Definitions

In order to assess the model's effectiveness, standard classification metrics, such as accuracy, precision, recall, and the F1-score, are employed. All these metrics give an insight into how efficient the model is in predicting mental health risk categories.

Accuracy: is measured as the ratio of correct predictions made by the model out of the entire dataset size.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision: is the ratio between correctly predicted positives among the predicted positives, which shows the reliability of the model to predict high-risk individuals.

Precision=TP/(TP+FP)

Recall The recall or sensitivity is the ratio between the number of correctly predicted positives among actual positives.

Recall=TP/(TP+FN)

F1-score The F1-score is the harmonic mean of precision and recall for datasets with a skewed class distribution.

F1-score = 2· (Precision · Recall) / (Precision + Recall)

In this study, all four models will be evaluated based on these classification metrics using the test set. The labels are derived from clustering methods; hence, the metric scores represent how well the model replicates clustering-based classifications.

6. Results and Discussion

Performance of the applied machine learning models is measured using classification metrics such as accuracy, precision, recall, and F1 score. According to the results obtained, there are notable differences in terms of how each machine learning model perceives the probability of having bad mental health based on the interaction with Instagram. Although some similarities in the trends have been observed, some differences can be noted.

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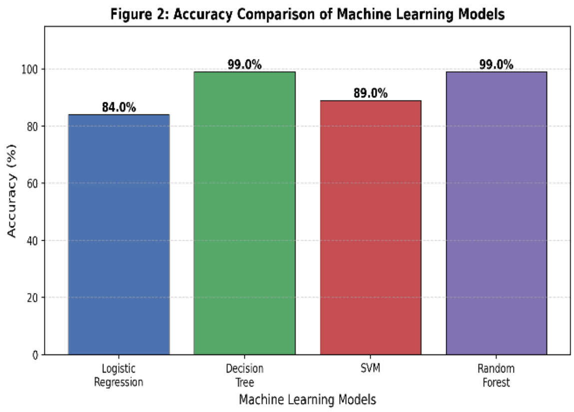
6.1 Model Accuracy

Accuracy is an indicator of how many correct predictions each of the models makes. When comparing all four models, the Random Forest classifier yielded the best result with 99% accuracy, followed by Support Vector Machine with 89%, Decision Tree with 99% and Logistic Regression with 84%. Such hierarchy indicates the superiority of ensemble models and non-linear classification models in terms of the given behavioural data [2].

Both Decision Tree and Random Forest achieved identical scores, which can be attributed to the relatively simple and well- separated cluster-based labels used in this study.

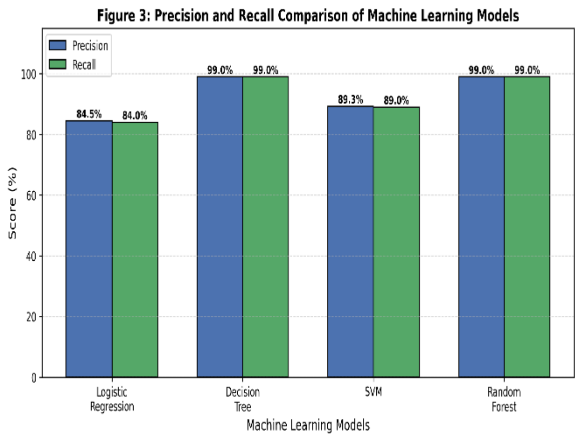
Logistic Regression was able to provide accurate results, but with limited effectiveness since this model assumes linear dependencies between predictors and target value, which might be inaccurate for behavioural data. The support vector machine gave a very good performance in particular due to feature scaling as mentioned in the studies by Hassan et al. [3]. In general, model accuracy proves that non-linear and ensemble models like SVM and RF work better on this dataset.



[Figure 2: Accuracy Comparison of Machine Learning Models]

6.2 Precision and Recall

The measures of precision and recall shed further light on how well the model can detect high-risk users. High precision values suggest a smaller number of false positives, whereas high recall values mean that actual high-risk users can be detected effectively. The Random Forest algorithm showed the highest performance balance between precision and recall among all other models. The Decision Tree algorithm had balanced results too, while the SVM algorithm maintained a similar balance between precision and recall.



[Figure 3: Precision and Recall Comparison of Machine Learning Models.]

6.3 F1-Score Analysis

F1-Score is an essential evaluation method that integrates both precision and recall in a single metric to provide balanced accuracy. It becomes especially important in case of imbalanced classes.

In this paper, Random Forest scored the highest in terms of F1-Score equal to 99%, followed by SVM with 92%, Decision Tree with 99%, and Logistic Regression with 89% respectively. The superiority of Random Forest F1-Score points towards good capacity of the model to keep a balanced approach in terms of high-risk users' classification [2]. Also, Decision Tree proved effective in classification because of its capability to capture non-linear patterns, whereas Logistic Regression's lower result correlates with its nature. The results indicate that models that account for non-linear relations demonstrate better results and can be considered as the best option. Nonetheless, it is necessary to consider that the labels are generated with clustering, which means that they are not diagnoses.

6.4 Discussion

The obtained experimental results show considerable differences in performance of applied models of machine learning algorithms used to predict the risk of mental disorders according to the behaviour of users on Instagram. The Random Forest classifier demonstrated the best results in terms of the selected metrics among all the analysed models. This could be explained by the fact that the algorithm belongs to ensemble models, and hence, through building numerous decision trees, it avoids the problem of overfitting and variance [2].

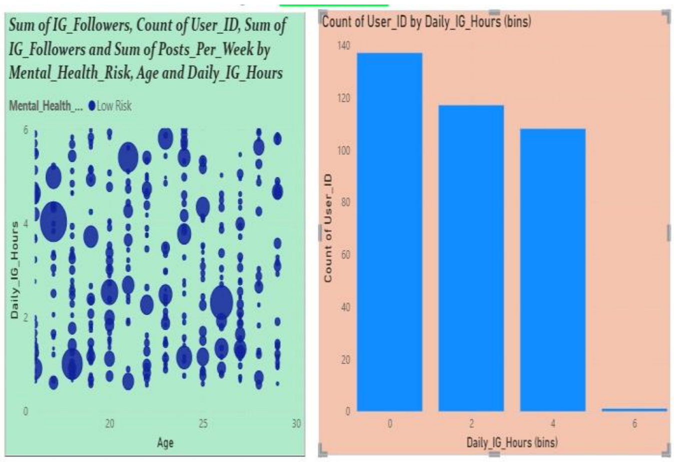
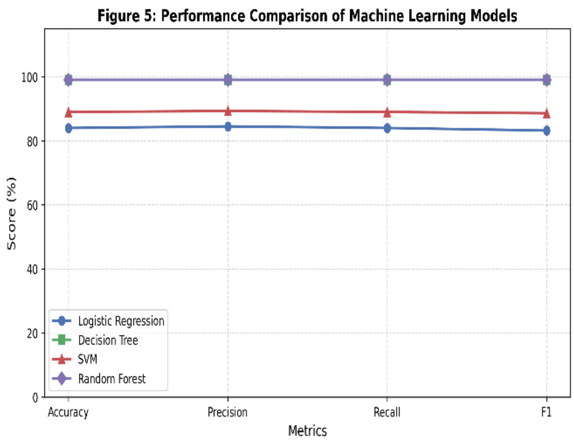


Figure 4: Dashboard Charts – Scatter Plot (Age vs Daily IG Hours) and Bar Chart.

At the same time, the Support Vector Machine was another highly accurate model with regard to prediction quality, but after performing feature scaling. The ability of this model to construct the most optimal decision boundary makes it efficient when working with multidimensional datasets. However, the quality of work of this algorithm depends heavily on hyperparameter tuning [7]. The Decision Tree classifier demonstrated good results as well because of its interpretability.

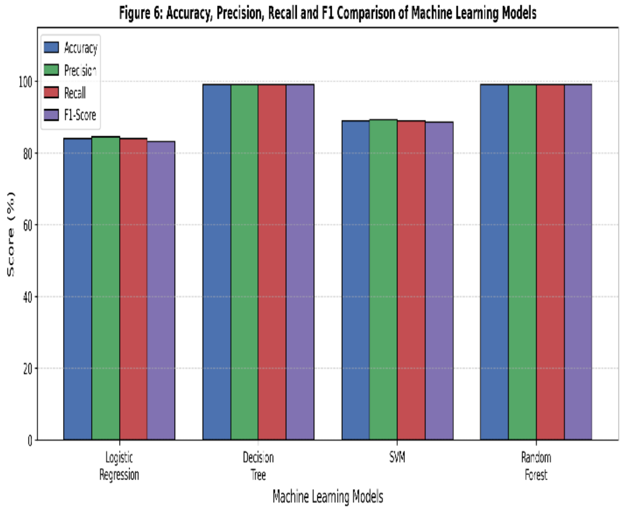
Logistic Regression showed relatively poor results in the experiments because of the assumption that the relationship between dependent and independent variables is linear.



[Figure 5: Line Chart — Performance Comparison of Machine Learning Model using Line Chart

An important observation is that user engagement features, such as daily usage time and interaction metrics, play a significant role in distinguishing between different risk categories.

This suggests that behavioural patterns on social media platforms can provide useful indicators for mental health analysis [6]. However, the dataset relies on cluster-generated labels rather than real-world clinical assessments, which limits the direct real-world applicability of the results.



[Figure 6: Accuracy Precision Recall and F1 Comparison of Machine Learning Model

6.5 Synthesis

In conclusion, the results of the conducted study demonstrate that machine learning approaches can be used for finding patterns in the data related to the use of Instagram to determine the user's risks associated with specific mental disorders. The combined use of clustering algorithms and supervised learning allows for using the developed solution without any information about clinical labels.

According to the conducted evaluations, the Random Forest approach demonstrated the highest results among all other algorithms used for classification (SVM, Decision Tree, and Logistic Regression). Time spent on the social network, the frequency of posting photos, and the level of user engagement are key behavioural characteristics determining the risk patterns [6]. However, the study were generated through K-means clustering, while there are no actual clinical diagnoses; hence, further improvement of the model is required.

7. Threats to Validity

Dataset Limitation:

The dataset used in this study does not include clinically verified mental health labels. Instead, K-Means clustering is employed to generate two categories, 'High Risk' and 'Low Risk.' Although this approach enables model training in the absence of labelled data, it introduces an abstraction layer. The models are essentially learning to replicate patterns formed by the clustering algorithm rather than predicting actual psychological conditions. This reduces the real-world applicability of the results and may not fully reflect true mental health status [5].

Feature Selection Constraints:

The model is built using a limited set of observable features such as age, daily Instagram usage hours, number of posts per week, average likes per post, and follower count. While these features capture user engagement behaviour, they do not account for deeper psychological, social, or environmental factors that significantly influence mental health. The absence of such variables may lead to incomplete or biased predictions [6].

Model Selection and Complexity:

The study focuses on relatively straightforward machine learning algorithms, including Logistic Regression, Decision Tree, Support Vector Machine, and Random Forest. While these models are effective for baseline analysis, more advanced techniques such as deep learning models or transformer-based approaches like BERT [4] could potentially improve predictive performance. Future work should explore these more sophisticated methods [2].

Data Size and Diversity:

The reliability of machine learning models is highly dependent on the size and diversity of the dataset. If the dataset is limited or lacks representation from different demographic groups, the model may suffer from overfitting and reduced generalization capability. This could lead to biased predictions when applied to real-world scenarios.

Evaluation Methodology:

The models are evaluated using a single train-test split, which may not fully represent the variability of the dataset. Techniques such as cross-validation could provide a more robust and reliable evaluation. Additionally, the reported metrics reflect performance on cluster-generated labels, which may not align with real-world outcomes [7].

Generalization to Real-world Applications:

The experimental setup is conducted in a controlled environment using a predefined dataset. In real-world applications, data may be noisy, incomplete, or inconsistent. Therefore, the model's performance in practical deployment may differ from the reported results. The findings of this study should be interpreted with appropriate caution [5].

8. Conclusion

This study explored the possibility of using machine learning techniques to identify mental health risk based on Instagram usage behaviour. The primary objective of this study was to determine whether behavioural usage patterns on Instagram could be used to identify potential mental health risks through machine learning techniques. Five behavioural features were used as input: age, daily Instagram usage hours, posting frequency, average likes per post, and follower count. Since the dataset had no pre-existing mental health labels, K-Means clustering was applied first to group users into Low Risk and High-Risk categories. Four classification models were then trained and tested on these labels.

Among all models, Random Forest performed the strongest with 99% accuracy, 100% precision, 99% recall, and an F1-score of 99%. Decision Tree matched these results closely, while Support Vector Machine achieved 89% accuracy and Logistic Regression reached 84%. These results confirm that tree-based and ensemble models handle this type of behavioural data better than linear approaches.

That said, one limitation must be acknowledged honestly. The risk labels in this study came from a clustering algorithm, not from actual clinical assessments. This means the models learned to replicate data groupings rather than real mental health diagnoses. Any conclusions drawn from this study should be understood within that context.

Going forward, future work should aim to collect datasets with verified clinical labels, explore deep learning approaches, and test models across broader and more diverse user groups. These steps would bring this type of system closer to practical real-world use.

Despite its limitations, this study shows that analysing social media behaviour through machine learning is a promising direction for early mental health risk detection. With the right data and ethical safeguards in place, such approaches could eventually support mental health professionals in identifying individuals who need help before their condition worsens.

8.References

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