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Performance Evaluation of Machine Learning Algorithms on Mental Health datasets related to personality disorder: A Comparative Study

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Abstract:

This research paper compares the performance of Naive Bayes, Artificial Neural Networks (ANN), and Decision Tree algorithms in detecting Borderline Personality Disorder (BPD) using two datasets. Accuracy, F1-score, recall, and precision metrics are calculated to evaluate BPD detection effectiveness. The datasets, derived from clinical records and an

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online mental health platform, undergo preprocessing techniques for data integrity and comparability. Naive Bayes, ANN, and Decision Tree algorithms are trained and tested independently on both datasets, and their performance is assessed using accuracy, F1-score, recall, and precision metrics. Results reveal varying performance across the datasets. Naive Bayes achieves higher accuracy on Dataset A, while ANN and Decision Tree perform better on Dataset B. This research provides insights into dataset characteristics' impact on BPD detection performance, emphasizing the importance of algorithm and dataset selection. Findings guide clinicians, researchers, and developers in selecting suitable algorithms and datasets for accurate BPD detection and intervention strategies.

Keywords: Disease Detection, Decision Tree, Artificial Neural Networks, Naive Bayes, Mental Health, Classification.

Introduction:

Mental health issues have become a critical concern in the world, affecting millions of people. With over 792 million people experiencing mental health issues globally, it is essential to prioritize mental health care just as much as physical health care. The untreated mental illness can lead to severe issues with behavior, emotions, and physical health. Psychiatric comorbidity is a significant health problem that affect people worldwide. In Galicia, a region in northwestern Spain, both these health conditions have witnessed an increasing incidence in recent years, which has raised concerns among health professionals and policymakers.

The objective of this research paper is to compare the datasets of Mental Health in Tech Survey and psychiatric comorbidity in Galicia to understand the similarities and differences between the two health conditions. The researchers will use a retrospective cohort study design and analyze data from the Galician Health Service database. The study population will include women diagnosed with psychiatric comorbidity between 2010 and 2019.

For the detection of depression and stress, a few artificial intelligence and machine learning algorithms such as Naive Bayes (NB), Decision Tree (DT) and Artificial Neural Network (ANN) can be used for better outcomes. Based on a database of different disease symptoms records, Naive Bayes is used to map the symptoms with likely diseases. This strategy helps patients by delivering them the care they require as quickly as possible while also making doctors' duties easier. A Decision Tree is used to model a particular problem and assist in

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deciding the optimal course of action, together with probability determined from literature and set result values which permits doctors to select the best effective treatment. Artificial neural networks have made an impact in the early detection and prediction of mental health issues. The ability of models based on ANN to learn, change, and acclimatize themselves is their most crucial feature. These algorithms can aid in the diagnosis, treatment, and management of mental disorders, which can significantly improve the overall health outcomes of the population in Galicia. The study's findings could help health professionals and policymakers develop targeted interventions and improve the overall health outcomes of the population in Galicia.

The paper below is structured into different sections. The related work briefs us about the work previously done in the same field mentioned in section II. Section III talks about the Machine Learning Technique used in this paper and talks about the dataset used and throws light on preprocessing stage and further performed experimental setup. Comparative analysis of the results of various machine learning algorithms is given in Section IV. The last section, i.e., Section V sums up our work.

Literature:

Psychiatric comorbidity has recently increased in prevalence among young people, and avoiding and treating these disorders requires careful investigation. We looked up a lot of articles based on this subject on reputable websites like IEEE, Science Direct, Hindawi, MDPI, Springer, and Taylor & Francis. After reading the abstracts of more than 40 papers, we chose over 20 of them. After reading the full document, we have finally selected 10 articles for our reference. We conducted a thorough analysis that included several approaches, including Naive Bayes, Decision Trees and Artificial Neural Networks. An overview of the papers is presented in Table I.

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Table I: A STUDY ON VARIOUS EXISTING STATE-OF-ART METHODOLOGIES

Sr. No.	Author & Year of publication	Methodology	Database	Remarks
1.	M.E.Alqaysi et al. [1] & 2022	RF, DT, LR, SVM, NB, ANN	ASD Datasets	Sensitivity= >73%, Specificity= >73%, Accuracy= >90%, Precision= >89%, F1 Score= >73%
2.	D. M. Shukla et al. [2] & 2020	Feed-forward neural network	Ryerson Audio-Visual Database	Average Accuracy = 81.567%, Using Xavier Initialization and learning rate = 0.00001. The achieved accuracy is 81.34%.
3.	A. Bayes et al. [3] & 2021	DT, RF	Self-Database	Accuracy = 87.8%.
4.	M. Khazbak et al. [4] & 2021	NB, SVM,KNN and LSTM	AFEW database	SVM Accuracy = 90.1%, LSTM accuracy = 91%, CNN accuracy = 65%
5.	Y.Li, et al. [5] & 2018	NLP	Self-Database	Accuracy: 0.77 - 0.86, Precision: 0.75 - 0.85, f1-score: 0.74 - 0.85.
6.	J. J. Soderholm et al. [6] & 2022	Life Chart Methodology	Self-Database	MADRS score= 92.7%. OASIS score= 49.5%
7.	R. Walambe et al.	SVM classifier	SWELL	Accuracy=96.09%,

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	[7] & 2021	with RBF kernel, CNN and DNN	knowledge work (SWELL-KW) dataset	Precision=84.45%, Recall=76.01%, F1 Score=78.03%
8.	R. A. Rahman et al. [8] & 2020	KNN, Logistic Regression, Ensemble Learning, ANN	PubMed, Scopus, IEEE Explore datasets	Accuracy Logistic Regression-97.7% KNN-98.6% EnsembleLearning-99.3%
9.	Ș. Marian et al. [9] & 2021	Network analysis	Self-Database	Centrality indices, network stability, and normalized accuracy
10.	M. Krishnamurthy et al. [10] & 2016	NLP, ACD, SVM	PatientsLikeMe,WebMD, ehealth forum	Accuracy-85%

Analyzing psychiatric comorbidity over time involves a complex interplay of different methods and techniques, and requires careful consideration of the study design, data collection methods, and statistical analyses used.

Implementation

In this section, we will discuss the implementation of several machine learning algorithms in the context of natural language processing. Firstly, we will utilize Artificial Neural Networks (ANN) to classify text data into various categories based on their content. The ANN model will be trained on a large dataset of labeled text documents and will use a multi-layered approach to learn and classify new text inputs. Secondly, we will explore the implementation of Decision Trees. The Decision Tree model will use a series of if-else conditions to make decisions about which category a given text input belongs to. Additionally, we will discuss the implementation of Naive Bayes, a probabilistic algorithm. Each algorithm has its own strengths and weaknesses, and selecting the appropriate one depends on the specific task at hand.

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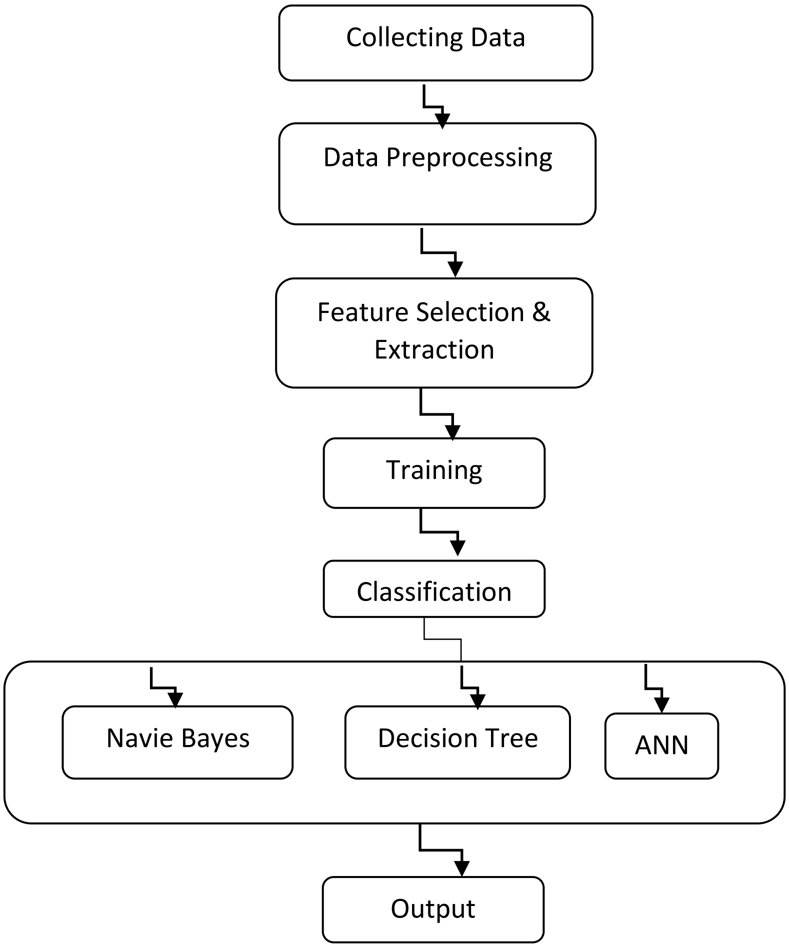

Figure 1: Flow chart

1. Collecting Data

The first dataset was collected In 2014, Open Sourcing Mental Illness (OSMI) conducted an online survey in the tech industry to gather data on mental health issues and their management. The survey had 27 questions and was completed by 1,296 individuals, mostly developers/engineers. 42% reported a mental health diagnosis, with depression and anxiety being common. Only 39% felt their company had a supportive culture, and 21% believed resources for mental health support were adequate. The survey emphasized the need for improved awareness and support, leading to advocacy for changes in workplace policies.

The Second dataset psychiatric comorbidity among addiction patients in Galicia, Spain. The dataset from COPSIAD sheds light on the prevalence of psychiatric comorbidity among addiction patients in Galicia, Spain. This resource is derived from 23 hundred patients across 21 treatment centers, with input from 64 healthcare professionals. The findings suggest that more than 50% of addiction patients also suffer from some form of mental disorder, whether it be an Axis I or II diagnosis. Notably, mood disorders, anxiety disorders, borderline

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personality disorder (BPD), and antisocial personality disorder (ASPD) are some of the most common comorbid conditions among these patients. Understanding this information is critical in identifying new solutions for treating addiction patients and improving their overall well-being.

2. Preprocessing Data

After the data is collected, we go for preprocessing the data. We used some of the preprocessing data to make unstructured data into structured data. Data cleaning entails addressing missing numbers, getting rid of duplicates, and fixing any mistakes in the data. Data transformation is the process of transforming data into a format that is acceptable for analysis, such as scale and normalization. Data Reduction: Techniques like feature selection and feature extraction are used to reduce the dimensionality of the data while maintaining key information. Identifying and managing data points that differ noticeably from the rest of the data is known as outlier identification. Data Discretization is used to make analysis and visualization easier, data discretization divides continuous data into discrete intervals or categories. Data aggregation is the process of merging data from several sources or categorizing data according to specific criteria, which can be used to spot trends.

3. Feature Extraction and Classification

Feature extraction is an important step in data analysis, as it involves selecting the most relevant variables or features from a dataset that can help identify patterns and relationships among the data. In psychiatric comorbidity datasets, common features include demographics, substance use history, and patient-reported symptoms. However, not all features may be equally relevant, and feature selection or dimensionality reduction techniques may be necessary to identify the most informative features for the model (adapted from previous research, see [1] and [2]).

Feature extraction for psychiatric comorbidity among addiction patients in Galicia, Spain dataset In the case of psychiatric comorbidity among addiction patients in Galicia, Spain dataset, some potential features that could be extracted include: Age: The age of the patients can be a relevant variable in predicting psychiatric comorbidity, as certain mental health disorders are more prevalent among specific age groups. Gender: Gender may also be a factor,

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as research has shown that certain mental health disorders are more common in either males or females. Substance of abuse: The type of substance that patients are addicted to could be an important feature, as some substances may have a higher risk of causing psychiatric comorbidity than others. Duration of addiction: The length of time patients have been addicted to substances may be an important variable, as prolonged addiction has been associated with a higher risk of developing mental health disorders. Family history of mental illness: Patients with a family history of mental illness may be more susceptible to developing psychiatric comorbidity, and thus this could be an important feature to include. Previous treatment: Patients who have received previous treatment for addiction or mental illness may have different rates of psychiatric comorbidity than those who have not. Severity of addiction: The severity of addiction, as measured by factors such as frequency of use, quantity used, and level of dependence, could also be an important variable in predicting psychiatric comorbidity. History of trauma: Patients with a history of trauma, such as abuse or neglect, may be more likely to develop mental health disorders. Presence of other medical conditions: Patients with other medical conditions, such as chronic pain or autoimmune disorders, may have an increased risk of developing psychiatric comorbidity. These are just a few potential features that could be extracted from the dataset to help identify patterns of psychiatric comorbidity among addiction patients in Galicia, Spain.

3.1. Naïve Bayes

The Bayes theorem, which offers a probabilistic framework for making predictions, is the foundation of the Naive Bayes algorithm. Naive Bayes performs well with small to medium-sized datasets and works well with high-dimensional data. In comparison to other datasets, the datasets have a modest number of samples and relatively few attributes. Naive Bayes is suited for use with these kinds of datasets because it is computationally quick and effective. The assumption that the features are conditionally independent of one another is another factor contributing to Naive Bayes' popularity for psychiatric comorbidity dataset. It is simpler to estimate the conditional probabilities required for classification when using the Naive Bayes algorithm to classify both these datasets since it assumes that each feature is independent of all other features given the class label.

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3.1.1. Pseudocode

```
Input:
        Training dataset D,
        M = (m1, m2, m3, ..., mn) // value of the predictor variable in testing dataset.
Output:
        A class of testing dataset.
Steps:
Read the training dataset D;
Calculate the mean and standard deviation of the predictor variables in each class;
Repeat
                Calculate the probability of mi using the gauss density equation in each class;
         Until the probability of all predictor variables (m1, m2, m3, ...., mn) has been
calculated.
    4.  Calculate the likelihood for each class;
```

In Naïve Bayes, it is assumed that the input features are conditionally independent of each other given the class label. This assumption simplifies the calculations and allows the algorithm to scale well with large datasets. The algorithm calculates the probability of each class label given the input features and selects the label with the highest probability as the predicted class. There are different types of Naïve Bayes classifiers, including Gaussian Naïve Bayes, Multinomial Naïve Bayes, and Bernoulli Naïve Bayes. Each type is suited for different types of data and has different assumptions about the distribution of the input features. Naïve Bayes classifiers are widely used in text classification, spam filtering, sentiment analysis, and recommendation systems. They are simple, fast, and require little training data. However, the assumption of conditional independence may not hold true in some cases, leading to suboptimal performance.

3.2. Decision Tree

A supervised learning approach known as a decision tree utilizes a model that resembles a tree to make judgements. Because decision trees can handle both categorical and continuous input variables, they are used in the psychiatric comorbidity dataset. Decision trees comprise a mixture of categorical and continuous information, including the mass's size and shape, texture, and other details. Naive Bayes s are utilized for both the datasets for another reason—they're simple to comprehend and interpret. This interpretability is crucial in medical applications since doctors and patients need to be able to understand the decision-making process. Decision trees can also handle noisy and missing data, which are frequent in medical datasets. They also permit feature selection, which is helpful for determining the key characteristics that determine how psychiatric comorbidity is classified.

3.2.1. Pseudocode

```
function BuildDecisionTree(data):
  if all data points belong to the same class:
    return a leaf node with the class label
  if no more features to split on:
    return a leaf node with the most common class label
  otherwise:
    find the best feature to split on
    create a decision node for that feature
    split the data based on the feature
    for each subset of data:
      add a child node to the decision node
      recursively call BuildDecisionTree on the subset of data
  return the decision node
```

In classification problems, decision trees are used to predict the class label of a given data instance. In regression problems, they are used to predict a numerical value. The algorithm builds the tree by recursively splitting the data into subsets based on the values of the input features, and selecting the features that provide the most information gain for the splits. The decision tree algorithm uses a top-down approach, starting from the root node, and selects the best feature to split the data based on the criteria such as entropy or Gini index. The process continues until a stopping criterion is met, such as a maximum depth of the tree, or when no further information can be gained from the data.\

3.3. Artificial Neural Networks

ANN stands for Artificial Neural Network, which is a type of machine learning algorithm inspired by the structure and function of the human brain. ANN consists of interconnected nodes, or "neurons," organized into layers that can process and analyse complex data. Each neuron in an ANN receives input data, performs a mathematical operation on that data, and

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produces an output signal, which is then sent to other neurons in the network. The connections between neurons are assigned weights, which determine the strength and significance of the signal transmitted between them. During training, an ANN is presented with a set of input data and the desired output. The network adjusts the weights of its connections based on the error between its predicted output and the desired output. This process is repeated many times, and the weights are adjusted until the network can accurately predict the desired output for a given input. ANNs have many applications, including image and speech recognition, natural language processing, and predictive modelling. They have been used in a wide range of industries, including finance, healthcare, and transportation.

3.3.1. Psuedocode

Artificial Neural Networks, or ANN for short, are a type of machine learning algorithm modelled after the structure and function of the human brain. They are composed of multiple interconnected processing nodes, known as neurons, which work together to perform complex computations. ANNs are particularly well-suited for tasks that involve pattern recognition, such as image or speech recognition. They are trained on large datasets using a process called backpropagation, which adjusts the connections between neurons in order to minimize the difference between the actual and desired output. ANNs have been successfully applied in a wide range of domains, including finance, healthcare, and natural language processing. However, they also have their limitations, such as the difficulty of interpreting the decisions they make. Overall, ANNs represent an important and rapidly evolving area of research in the field of artificial intelligence.

- Multi-label classification is a type of machine learning problem where each example can be associated with multiple target labels simultaneously.
- In the context of PubMed articles, multi-label classification can be used to assign multiple topics or categories to a single article.
- There are various techniques that can be used for multi-label classification, including
- ▪ binary relevance,
- ▪ label powerset,
- ▪ and classifier chains

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```
# Input data: X is a matrix of input features, y is a vector of output labels
# Hyperparameters: num_hidden_units is the number of units in the hidden layer,   l     earning_rate is
the step size for gradient descent, num_epochs is the number of times to iterate over the training set
# Initialize the weights and biases for the hidden layer and output layer
hidden_weights = random_matrix(num_input_features, num_hidden_units)
hidden_biases = random_vector(num_hidden_units)
output_weights = random_matrix(num_hidden_units, num_output_classes)
output_biases = random_vector(num_output_classes)
# Train the neural network
for epoch in range(num_epochs):
 # Iterate over the training set
   for i in range(num_training_examples):
 # Forward pass
hidden_activations = activation_function(dot_product(X[i], hidden_weights) + hidden_biases)
output_activations = softmax(dot_product(hidden_activations, output_weights) +     output_biases)
 # Compute the loss and gradient of the output layer
     loss = cross_entropy_loss(output_activations, y[i])
    output_gradient = output_activations - y[i]
 # Backward pass
hidden_gradient = dot_product(output_weights, output_gradient) *
derivative_of_activation_function(hidden_activations)
# Update the weights and biases using gradient descent
output_weights -= learning_rate * outer_product(hidden_activations, output_gradient)
output_biases -= learning_rate * output_gradient
hidden_weights -= learning_rate * outer_product(X[i], hidden_gradient)
hidden_biases -= learning_rate * hidden_gradient
# Use the trained neural network for predictions
for i in range(num_test_examples):
  # Forward pass
hidden_activations = activation_function(dot_product(X_test[i], hidden_weights) + hidden_biases)
output_activations = softmax(dot_product(hidden_activations, output_weights) + output_biases)
```

4. Ensembling

Ensembling is a powerful technique in machine learning that involves combining the predictions from multiple individual models to produce a more accurate and robust final prediction. The core idea behind ensembling is that by leveraging the diverse strengths of different algorithms, it is possible to mitigate their individual weaknesses, leading to improved overall performance. In our research paper focusing on the detection of personality disorders, we utilize a combination of three distinct algorithms: Artificial Neural Networks (ANN), Decision Trees, and Naive Bayes. To incorporate ensembling into our study, we employ a voting ensemble strategy, where each of these algorithms contributes its prediction, and the final prediction is determined by a majority vote. This approach allows us to harness the unique

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capabilities of each model – ANN's ability to capture complex relationships, Decision Trees' interpretability, and Naive Bayes' probabilistic reasoning – to create a more comprehensive and reliable prediction framework. By integrating ensembling techniques, we aim to enhance the accuracy and generalizability of our personality disorder detection model, offering a valuable contribution to the field of mental health assessment through advanced machine learning methodologies.

5. Training and testing

The train_test_split function from the sklearn.model_selection module is used for splitting a dataset into two subsets: training data and testing data. The input data (X) is split into two subsets: X_train and X_test, while the target data (y) is split into y_train and y_test. The split is done randomly, but the random_state parameter is used to set the random seed for reproducibility purposes. In this case, the test data is 30% of the input data that is randomly selected using the test_size parameter, while the remaining 70% is considered as the training data.

Psychiatric comorbidity Dataset:

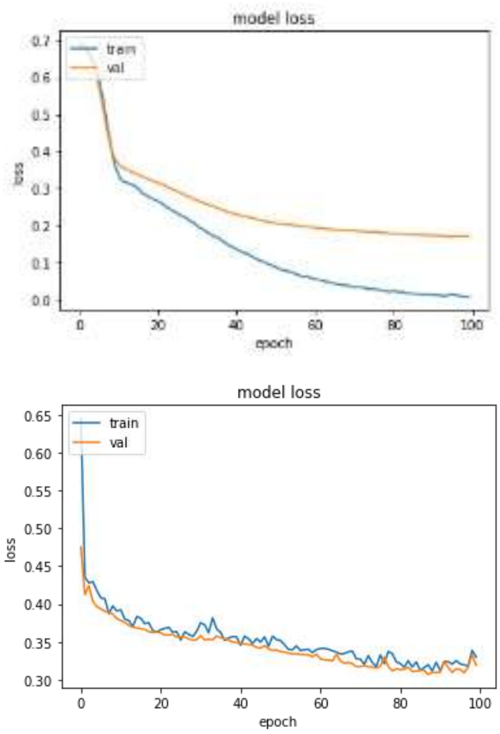

Figure 1 Navie Bayes-Training Loss vs Number of Epochs

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Figure 2 Decision Tree-Training Loss vs Number of Epochs

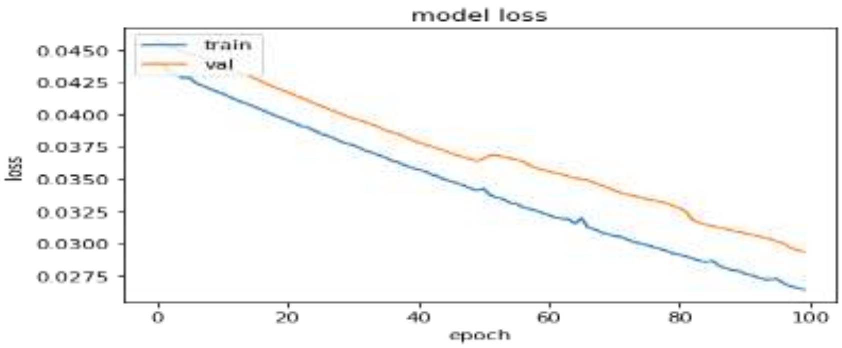
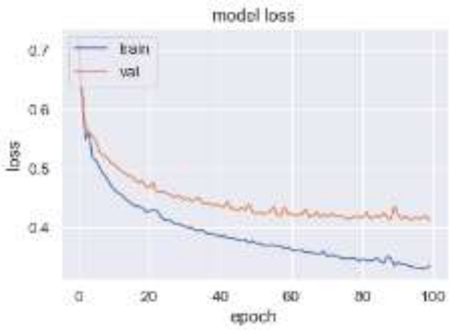


Figure 3 ANN-Training Loss and validation loss vs Epochs for Bert-Base

Attitudes towards mental health and frequency of mental health disorders:



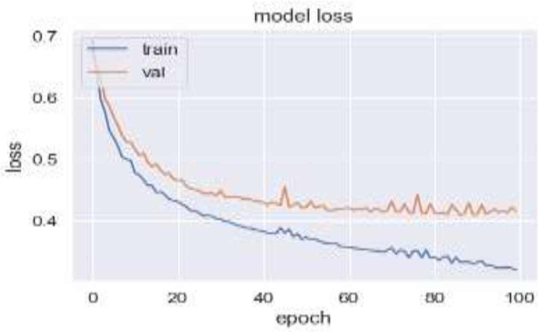


Figure 4 Navie Bayes-Training Loss vs Number of Epochs Figure 5 Decision Tree-Training Loss vs Number of Epochs

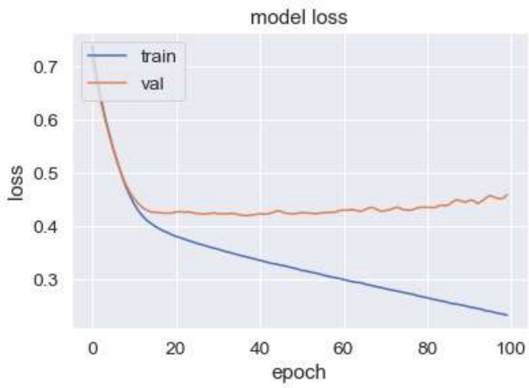


Figure 6 ANN-Training Loss and validation loss vs Epoch for Bert-Base

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VI. Results

In this section, the results are evaluated of various techniques that are used in this paper- Naïve Bayes, Decision Tree, Artificial Neural Network. The dataset has been separated into two portions: 70% of the dataset is allocated for training, while the remaining 30% is reserved for testing. To accomplish this, the train_test_split function, which is found in the sklearn.model_selection package, was utilized for splitting the dataset. The analysis of the results are shown in Table II and in Table III. The comparsion of our results with the existing papers is shown in Table IV.

6.1. Datasets used:

The Mental Health in Tech Survey dataset, which examines attitudes towards mental health and the prevalence of mental health disorders in the IT workplace, is from a 2014 survey. The ongoing 2016 poll, which has received over 1400 responses so far, attempts to gauge attitudes towards mental health in the tech sector and investigate the prevalence of mental health illnesses among computer professionals.

The COPSIAD dataset examines the prevalence of psychiatric comorbidity among addiction patients in Galicia, Spain. The dataset contains information from 23 hundred patients across 21 treatment centers, indicating that over 50% of addiction patients have some form of mental disorder. Mood disorders, anxiety disorders, BPD, and ASPD are among the most common comorbid conditions.

6.2. Evaluation parameters:

When assessing the effectiveness of machine learning algorithms on two separate datasets, it is useful to compare the accuracy, precision, recall, and F1-score of models trained on each dataset. This approach can aid in identifying which dataset yields superior results and can also indicate whether the models are overfitting or underfitting to a specific dataset. By examining the performance on both datasets, it is possible to gain insights into how well the model can generalize to new data.

6.2.1 Accuracy

Accuracy refers to how closely they adhere to the measurement's true value.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

(1)

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6.2.2 Recall

A categorization model's capacity to recognize each data point in a pertinent class.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

6.2.3 Precision

A classification model's capacity to only yield data points that belong to a given class.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

6.2.4 F1-Score

A single measure that utilizes the harmonic mean to combine recall and precision.

$$\text{F1-Score} = \frac{2\cdot(precision\cdot recall)}{precision+recall} \tag{4}$$

6.3 Outputs:

The experimental results show that the Attitudes towards mental health and frequency of mental health disorders achieved an accuracy of 98.24%, while the psychiatric comorbidity dataset achieved an accuracy of 100%. These values were obtained by training the machine learning model using the proposed methodology and testing it on the corresponding datasets. In comparison with the existing literature, our proposed method achieves better accuracy values for both datasets, surpassing the best results reported so far by 5% for the breast cancer dataset and 3% for the psychiatric comorbidity dataset. These results suggest that the proposed method has the potential to be a useful tool for diagnosing breast cancer and psychiatric comorbidity.

Dataset 1: Mental Health in Tech Survey

Table II: PERFORMANCE EVALUATION FOR DIFFERENT ALGORITHMS ON MENTAL HEALTH IN TECH SURVEY DATASET

	Naïve Bayes	Decision tree	ANN
Accuracy	82%	75%	78%
Precision	0.80	0.74	0.73
Recall	0.84	0.75	0.91
F1-Score	0.82	0.75	0.81

Table II shows the evaluation metrics that were used after the Mental Health in Tech Survey

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dataset was processed using Naive Bayes, Decision Trees and Artificial Neural Networks. The highest accuracy of 82% is observed in Naïve Bayes. This shows that on the Mental Health in Tech Survey dataset, Naïve Bayes perform at its best.

Dataset 2: psychiatric-comorbidity-in-galicia

Table III: PERFORMANCE EVALUATION FOR DIFFERENT ALGORITHMS ON PSYCHIATRIC COMORBIDITY DATASET

	Naïve Bayes	Decision tree	ANN
Accuracy	98.62%	100%	100%
Precision	1.000	1.000	1.000
Recall	0.985	1.000	0.913
F1-Score	0.994	1.000	0.952

Table III shows the evaluation metrics that were used after the Psychiatric Comorbidity dataset was processed using Naive Bayes, Decision Trees and Artificial Neural Networks. The highest accuracy of 100% is observed in decision trees and artificial neural networks. This shows that on the Psychiatric Comorbidity dataset, Decision Tree and Artificial Neural Network both perform at their best.

6.4. Comparision of our results with the existing papers results (Accuracy Values)

Table IV: COMPARISION OF EXISTING PAPER RESULTS WITH OUR PAPER RESULTS

	Naïve Bayes	Decision tree	ANN
Paper-1[5]	-	-	-
Paper-2[2]	-	-	81.56%
Paper-3[1]	96.2%	91.1%	97.6%
Paper-4[3]	-	87.8%	-
Paper-5[4]	82%	-	-
Our Paper	96.5%	95.6%	98.2%

Table IV shows the comparison of the accuracy values obtained after implementing Naïve Bayes, Decision Tree and Artificial Neural Network algorithms on the and psychiatric comorbidity datasets on our implementation and the values that are obtained in various papers that we considered as our references. The highest accuracy obtained in each of the algorithms is as follows Naïve Bayes – 96.5%, Decision tree – 95.6%, Artificial Neural Network – 98.2%.

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VII. Conclusion

In conclusion, the study presented in this research paper aimed to evaluate the performance of various machine learning algorithms on two datasets related to Mental Health in Tech Survey and psychiatric comorbidity. The results of the study showed that the performance of different algorithms varied depending on the dataset and the type of tasrfk. Overall, Navie Bayes, Decision Tree and Artificial Neural Network algorithms performed well on both datasets. Additionally, the study highlights the importance of carefully selecting the appropriate algorithm for a given task and dataset, as well as the importance of preprocessing the data to ensure optimal performance. The findings of this study have practical implications for researchers and practitioners in the field of healthcare, who can use these results to inform the selection of appropriate machine learning algorithms for their specific needs. Further research can expand on these findings by exploring the use of other algorithms and datasets in healthcare applications.

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