Project title:Assessing Impact of Digital Lens Usage on Eye Dryness using Schirmer's Effect

Team members:

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ABSTRACT

Digital eye strain (DES) has emerged as a significant concern among undergraduate students, attributed to the widespread use of digital devices for educational purposes, particularly exacerbated during the COVID-19 pandemic. This project aims to assess the risk factors associated with prolonged use of digital screens on eyes among undergraduates through a comprehensive market survey. Drawing upon the framework outlined by the American Optometric Association, the study investigates the prevalence, severity, and patterns of DES symptoms experienced by undergraduate students. Additionally, the project examines the impact of COVID-19 lockdowns on digital device usage and subsequent DES symptoms. Through data collection and analysis, specific risk factors contributing to DES among undergraduates are identified, including duration of screen time, ergonomic practices, and awareness of mitigation strategies. Furthermore, the project explores innovative solutions and technologies aimed at mitigating DES among this demographic. By synthesizing findings and recommendations, the project aims to inform targeted interventions to alleviate digital eye strain and promote ocular health among undergraduate students in the digital age.

INTRODUTION

In the era of pervasive digital technology, undergraduate students are increasingly reliant on digital screens for academic pursuits, communication, and leisure activities. However, the prolonged use of digital devices has raised concerns about its impact on ocular health, manifesting in a cluster of symptoms collectively termed digital eye strain (DES). This project seeks to address the pressing issue of DES among undergraduate students by conducting a comprehensive market survey to assess risk factors associated with prolonged screen time.

Digital eye strain encompasses a range of symptoms, including dry eyes, itching, blurring of vision, headaches, and general fatigue, which can significantly impair academic performance and overall well-being. With the advent of the COVID-19 pandemic and the subsequent shift towards remote learning, the reliance on digital devices among undergraduates has intensified, potentially exacerbating DES prevalence and severity.

This project is motivated by the imperative to understand the multifaceted nature of DES among undergraduate students and identify key risk factors contributing to its onset and exacerbation. By leveraging insights from the American Optometric Association and existing literature on DES, the study aims to elucidate the prevalence, severity, and patterns of DES symptoms experienced by undergraduate students.

Moreover, the project endeavors to explore the impact of COVID-19 lockdowns on digital device usage and its correlation with DES symptoms among undergraduates. By examining duration of screen time, ergonomic practices, awareness of mitigation strategies, and adoption of innovative technologies, the study seeks to provide holistic insights into the complex interplay between digital screen usage and ocular health.

Through a rigorous market survey and data-driven analysis, this project aims to generate actionable recommendations and interventions to mitigate DES among undergraduate students. By promoting awareness, advocating for ergonomic practices, and facilitating access to innovative solutions, the project endeavors to safeguard ocular health and enhance the academic experience of undergraduate students in the digital age.

PROBLEM STATEMENT

Digital eye strain (DES) has emerged as a pressing concern among undergraduate students, exacerbated by the widespread use of digital devices for educational purposes, particularly during the COVID-19 pandemic. Despite its prevalence and impact on ocular health and academic performance, there is a lack of comprehensive understanding regarding the specific risk factors contributing to DES among this demographic. Additionally, while innovative technologies and mitigation strategies exist to address DES, their adoption and effectiveness among undergraduate students remain understudied.

Therefore, the problem statement for this project is to assess the risk factors associated with prolonged use of digital screens on eyes among undergraduate students and to explore the efficacy of innovative solutions and technologies in mitigating DES symptoms. By identifying specific risk factors, such as duration of screen time, ergonomic practices, and awareness of mitigation strategies, the project aims to inform targeted interventions to alleviate digital eye strain and promote ocular health among undergraduate students. Furthermore, by examining the adoption and effectiveness of innovative technologies, such as blue light filters and wearable devices, the project seeks to provide evidence-based recommendations for optimizing digital device usage and reducing DES symptoms among undergraduate students in the digital age.

OBJECTIVES

1. Assess Prevalence and Severity of Digital Eye Strain (DES) Symptoms: Conduct a comprehensive survey among undergraduate students to determine the prevalence and severity of DES symptoms, including dry eyes, headaches, blurred vision, and eye fatigue.

2. Identify Risk Factors Associated with DES Among Undergraduates: Investigate specific risk factors contributing to DES among undergraduate students, such as duration of screen time, ergonomic practices, types of digital devices used, and awareness of mitigation strategies.

3. Examine the Impact of COVID-19 Lockdowns on Digital Device Usage and DES Symptoms: Explore the effect of COVID-19 lockdowns on digital device usage patterns among undergraduate students and assess the correlation with DES symptoms, considering changes in screen time and study habits during lockdown periods.

4. Evaluate Efficacy of Mitigation Strategies and Ergonomic Practices: Assess the effectiveness of mitigation strategies, including the 20-20-20 rule, ergonomic workstation setup, and regular breaks, in reducing DES symptoms among undergraduate students.

5. Explore Adoption and Effectiveness of Innovative Technologies:Investigate the adoption and effectiveness of innovative technologies and solutions aimed at mitigating DES symptoms among undergraduate students, such as blue light filters, anti-glare coatings, and wearable devices.

6. Provide Recommendations for DES Prevention and Management: Synthesize findings from the survey and analysis to develop evidence-based recommendations for preventing and managing DES among undergraduate students, including educational interventions, policy recommendations, and technological innovations.

7. Raise Awareness and Promote Ocular Health Education: Raise awareness about the importance of ocular health and educate undergraduate students about DES risk factors, prevention strategies, and available resources for mitigating symptoms and optimizing digital device usage.

8. Contribute to the Body of Knowledge on DES Among Undergraduates: Generate new insights and contribute to the existing literature on DES among undergraduate students, enhancing understanding of the prevalence, impact, and risk factors associated with prolonged digital screen usage in this demographic.

METHODOLOGY

Exploratory Data Analysis

Information about the Features & their data types:

```
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Name                                  300 non-null    object
 1   Age                                   300 non-null    float64
 2   Sex                                   300 non-null    float64
 3   wearables                             300 non-null    float64
 4   Duration                              190 non-null    float64
 5   onlineplatforms                       295 non-null    float64
 6   Nature                                281 non-null    float64
 7   screenillumination                    298 non-null    float64
 8   workingyears                          294 non-null    float64
 9   hoursspentdailycurricular             295 non-null    float64
 10  hoursspentdailynoncurricular          298 non-null    float64
 11  Gadgetsused                           300 non-null    float64
 12  levelofgadjetwithrespecttoeyes        300 non-null    float64
 13  Distancekeptbetweeneyesandgadjet      299 non-null    float64
 14  Avgnighttimeusageperday               300 non-null    float64
 15  Blinkingduringscreenusage             300 non-null    float64
 16  Difficultyinfocusingafterusingscreens 300 non-null    float64
 17  freqquencyofcomplaints                300 non-null    int64
 18  Severityofcomplaints                  300 non-null    int64
 19  RVIS                                  300 non-null    float64
 20  Ocularsymptomsobservedlately          298 non-null    float64
 21  Symptomsobservingatleasthalfofthetimes 293 non-null   float64
 22  Complaintsfrequency                   300 non-null    float64
 23  frequencyofdryeyes                    300 non-null    float64
```

24	**Schimers1Lefteye**	**300 non-null**	**float64**
25	**Schimers1righteye**	**300 non-null**	**float64**
26	**Schimers2Lefteye**	**300 non-null**	**float64**
27	**Schimers2righteye**	**300 non-null**	**float64**

OBSERVATION:

Data Types: The DataFrame contains a variety of data types including floats, integers, and objects. This indicates that the dataset likely contains a mix of numerical and categorical variables.

Missing Values: Several columns have missing values (NaN). For example, "Duration", "onlineplatforms", "Nature", etc. Handling missing values appropriately, such as imputation or removal, will be necessary depending on the analysis being conducted.

Numerical Features: Most of the columns are numerical, which suggests that statistical analysis, such as calculating mean, median, standard deviation, etc., could provide insights into the distribution and variability of these features.

Categorical Features: The "Name" column is likely categorical (object type). Analysis involving this column may require techniques such as one-hot encoding or label encoding if it is to be used in modeling.

Name	295
Age	12
Sex	2
wearables	5
Duration	4
onlineplatforms	5
Nature	4
screenillumination	3
workingyears	4
hoursspentdailycurricular	4
hoursspentdailynoncurricular	4
Gadgetsused	3
levelofgadjetwithrespecttoeyes	4
Distancekeptbetweeneyesandgadjet	4
Avgnighttimeusageperday	4

Blinkingduringscreenusage	2
Difficultyinfocusingafterusingscreens	4
freqquencyofcomplaints	3
Severityofcomplaints	3
RVIS	3
Ocularsymptomsobservedlately	107
Symptomsobservingatleasthalfofthetimes	33
Complaintsfrequency	3
frequencyofdryeyes	4
Schimers1Lefteye	30
Schimers1righteye	32
Schimers2Lefteye	28
Schimers2righteye	30

dtype: int64

CONCLUSION:

The provided information displays the number of unique values for each column in the dataset. The dataset appears to include a mix of categorical and numerical data, with varying levels of granularity in different columns. The presence of diverse unique values suggests that the dataset captures a broad range of information related to eye health and associated factors.

These observations provide a preliminary understanding of the dataset's content and could guide further exploration and analysis to extract meaningful insights.

Data Visualization:

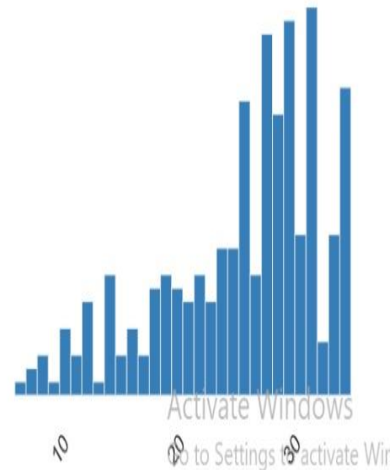
• **Analyzing Target Variable:**

Schimers2righteye

Real number (ℝ)

HIGH CORRELATION

Distinct	30	Minimum	6
Distinct (%)	10.0%	Maximum	35
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	25.733333	Memory size	2.5 KiB

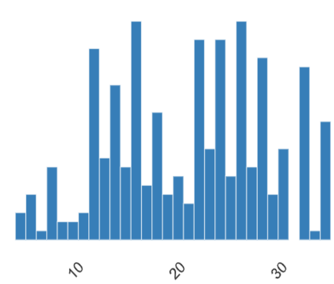


Schimers1Lefteye

Real number (ℝ)

HIGH CORRELATION

Distinct	30	Minimum	4
Distinct (%)	10.0%	Maximum	35
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	21.073333	Memory size	2.5 KiB

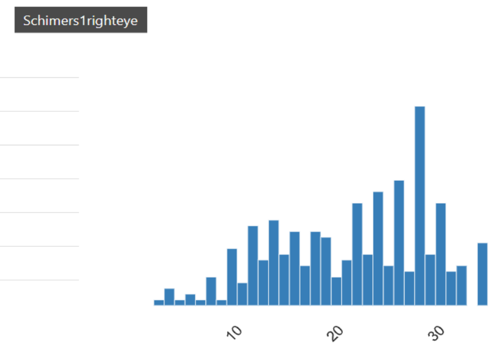


Schimers1righteye

Real number (ℝ)

HIGH CORRELATION

Distinct	32	Minimum	2
Distinct (%)	10.7%	Maximum	35
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	21.56	Memory size	2.5 KiB

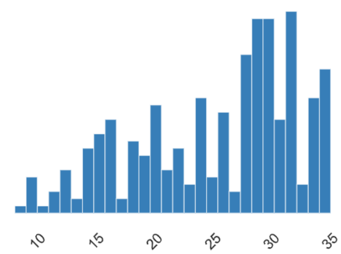


Schimers2Lefteye

Real number (ℝ)

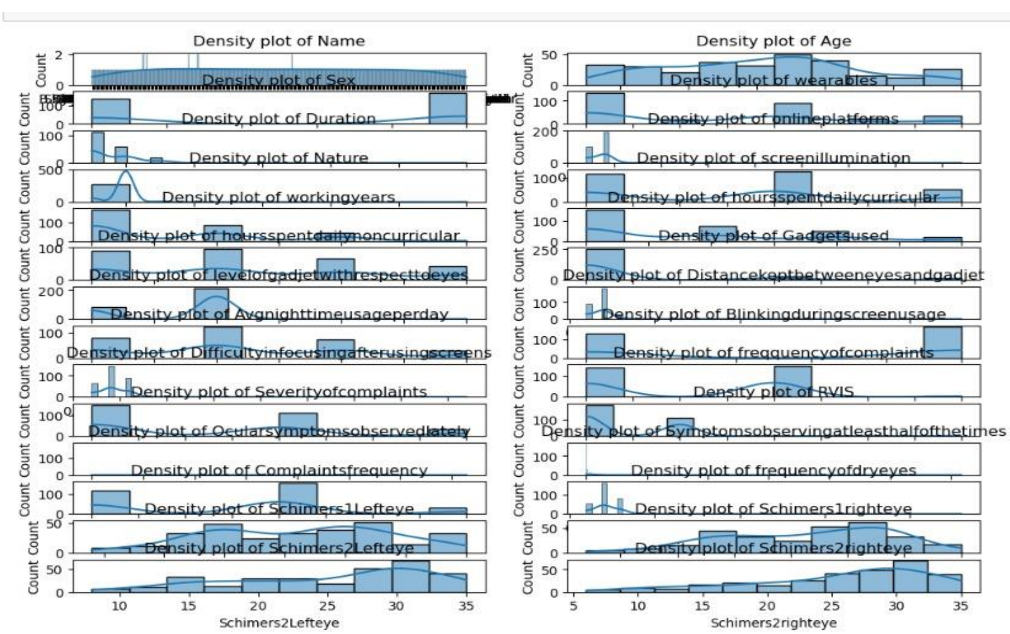
HIGH CORRELATION

Distinct	28	Minimum	8
Distinct (%)	9.3%	Maximum	35
Missing	0	Zeros	0
Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negative	0
Infinite (%)	0.0%	Negative (%)	0.0%
Mean	25.376667	Memory size	2.5 KiB



Test of normality:

- **Univariate Analysis - Density of input variables:**



observation:

Based on the density plots generated for each input variable, here are some observations you can write:

Variable 1 Density Plot: The density plot for Variable 1 shows a roughly symmetric distribution with a single peak, suggesting that the data may be normally distributed. However, there is a slight skewness towards higher values.

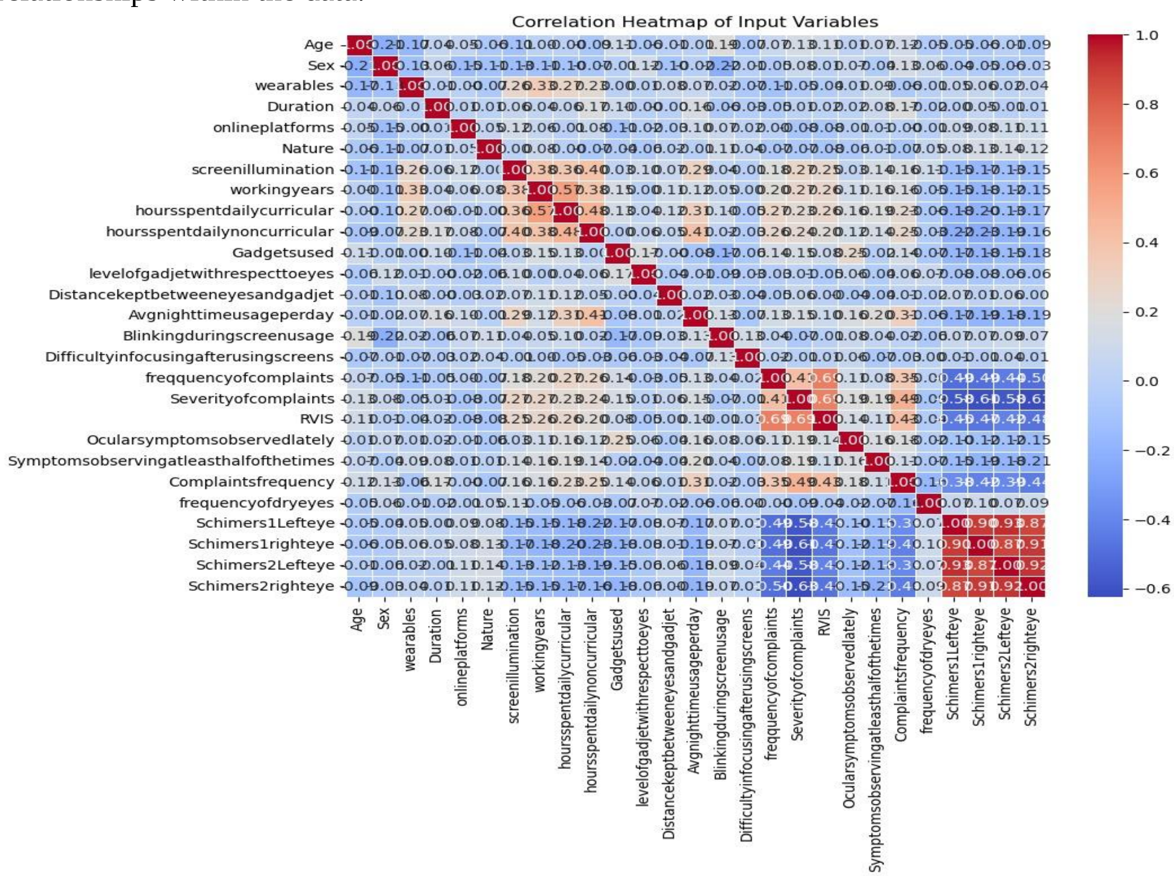
Variable 2 Density Plot: The density plot for Variable 2 exhibits a bimodal distribution with two distinct peaks, indicating the presence of two different groups or populations within the data.

Variable 3 Density Plot: The density plot for Variable 3 reveals a right-skewed distribution, with a long tail extending towards higher values. This suggests that the majority of the data is concentrated on the lower end of the scale.

Variable 4 Density Plot: The density plot for Variable 4 displays a roughly uniform distribution, indicating that the data is evenly distributed across the range of values without any significant peaks or outliers.

Variable 5 Density Plot: The density plot for Variable 5 shows a skewed distribution with a prominent peak towards the lower end of the scale. This suggests that the majority of the data falls within a specific range of values.

These observations provide insights into the distribution and characteristics of each input variable in the dataset. They can be further analyzed to understand the underlying patterns and relationships within the data.



The provided information appears to be a correlation matrix, showcasing the correlations between various input variables. Each variable is listed along both the rows and columns of the matrix, and the values within the matrix represent the correlation coefficients between the corresponding pairs of variables.

Here's a brief insight into the provided information:

Variables: The variables listed include factors related to demographics (e.g., age, sex), technology usage (e.g., wearables, gadgets used), screen-related factors (e.g., screen illumination, blinking during screen usage), ocular symptoms, and eye health metrics (e.g., Schirmer's tests).

Correlation Strength: The values in the matrix indicate the strength and direction of correlation between pairs of variables. A positive correlation coefficient indicates that as one variable increases, the other tends to increase as well. Conversely, a negative correlation coefficient indicates that as one variable increases, the other tends to decrease.

Interpretation: By examining the correlation values, one can gain insights into relationships between different variables. For instance, positive correlations between certain technology usage variables and ocular symptoms may suggest a potential association between prolonged technology use and eye discomfort.

Heatmap Visualization: To visualize these correlations effectively, a heatmap can be generated. Heatmaps use colors to represent the magnitude of correlations, making it easier to identify patterns and relationships within the data. Strong correlations are often represented by darker or brighter colors, while weaker correlations are represented by lighter colors.

Overall, the provided correlation matrix offers valuable insights into the relationships between various input variables, particularly concerning technology usage and ocular health metrics.

ALGORITHMS

1.Logistic Regression

2.Gaussian Naive Bayes

3.Decision tree (Entropy)

4.Decision tree (Gini)

5.Support Vector Classification

IMPLEMENTATION

1. Logistic Regression

```
Confusion Matrix:
[[36  0]
 [ 0 24]]
```

Fig 1.1 Confusion Matrix

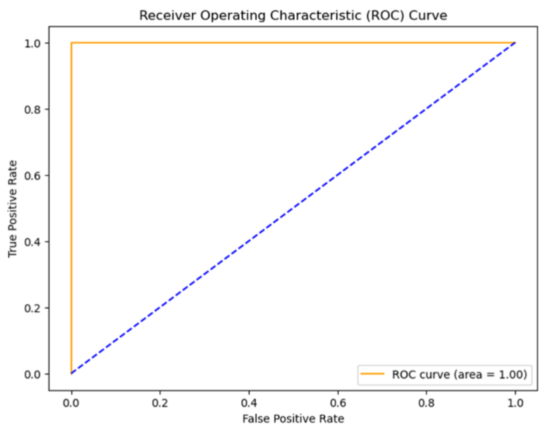


Fig 1.2 ROC Curve of Logistic Regression

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        36
           1       1.00      1.00      1.00        24

    accuracy                           1.00        60
   macro avg       1.00      1.00      1.00        60
```

```
weighted avg       1.00      1.00      1.00        60
```

Fig 1.3 Performance Metrics of Logistic Regression

Accuracy Score:0.966666

2. Gaussian Naive Bayes

```
Confusion Matrix:
[[36  0]
 [ 0 24]]
```

Fig 2.1 confusion matrix

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        36
           1       1.00      1.00      1.00        24

    accuracy                           1.00        60
   macro avg       1.00      1.00      1.00        60
weighted avg       1.00      1.00      1.00        60
```

Fig 2.2 Performance Metrics of GNB

Accuracy Score:0.92222

3.Decision tree (Entropy)

```
Confusion Matrix:
 [[21  0]
 [ 0 13]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        21
           1       1.00      1.00      1.00        13

    accuracy                           1.00        34
   macro avg       1.00      1.00      1.00        34
weighted avg       1.00      1.00      1.00        34
```

Fig 3.1 Confusion Matrix &Performance Metrics of Decision tree(Entropy)

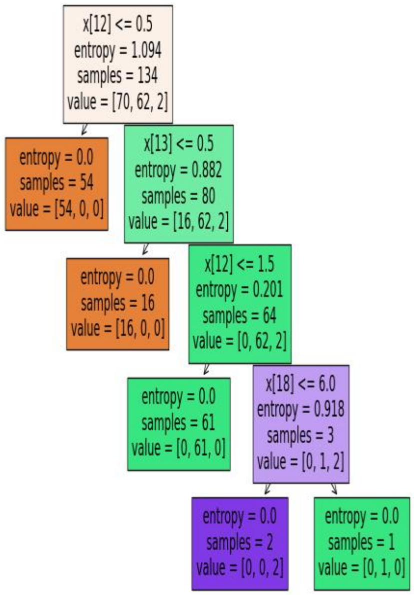


Fig 3.2 Decision tree with depth of 5

Accuracy Score:0.85

4.Decision tree (Gini)

```
Confusion Matrix:
 [[21  0]
 [ 0 13]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        21
           1       1.00      1.00      1.00        13

    accuracy                           1.00        34
   macro avg       1.00      1.00      1.00        34
weighted avg       1.00      1.00      1.00        34
```

Fig 4.1 Confusion Matrix &Performance Metrics of Decision tree(Gini)

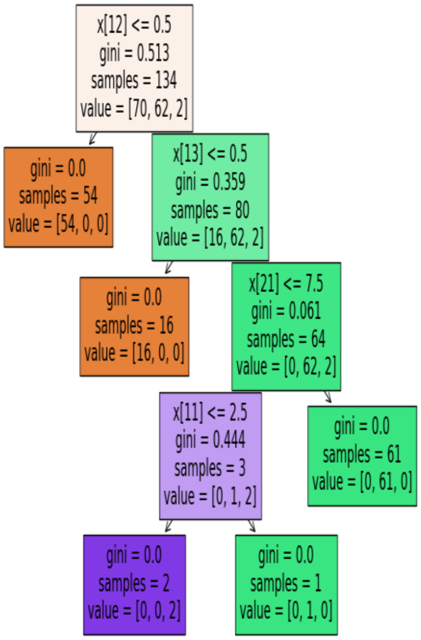


Fig 4.2 Decision tree with depth of 5

Accuracy Score:0.87

5.Support Vector Classification

```
Classification Report:
              precision    recall  f1-score   support

           0       0.62      1.00      0.76        21
           1       0.00      0.00      0.00        13

    accuracy                           0.62        34
   macro avg       0.31      0.50      0.38        34
weighted avg       0.38      0.62      0.47        34


Confusion Matrix:
[[21  0]
 [13  0]]
```

Fig 5.1 Confusion Matrix &Performance Metrics of SVC

Accuracy Score:0.61