# INTELLIGENT ADMISSION : THE FUTURE OF UNIVERSITY DECISION MAKING USING MACHINE LEARNING

#### 1.INTRODUCTION

1.1 Overview

A brief description about your project

1.2 Purpose

The use of this project. What can be achieved using this.

# 2.Problem Definition & Design Thinking

- 2.1 Empathy Map
- 2.2 Identification & Brainstorm Map
- 3.RESULT
- **4.ADVANTAGES & DISADVANTAGES**
- **5.APPLICATION**
- **6.CONCLUSION**
- **7.FUTURE SCOPE**
- **8.APPENIX**

# 1.1 Overview

The future of university decision making could involve the integration of machine learning algorithms to help university administrators make more informed decisions. This could include using data analysis and predictive models to identify trends and patterns in student enrollment, academic performance, and other important factors.

Machine learning algorithms could be trained to analyze large datasets and provide insights into which courses are most popular among students, which programs are most successful, and which initiatives are most effective in promoting student success.

These insights could then be used by university administrators to make informed decisions about resource allocation, program development, and other strategic initiatives. By leveraging the power of machine learning, universities could become more data-driven and responsive to the changing needs of their students and stakeholders.

# 1.2 PURPOSE

The use of machine learning in university decision making can have several benefits and help achieve various goals. Here are a few Potential outcomes of implementing such a project:

**Improved student outcomes**: By analyzing student data, such as enrollment patterns and academic performance, machine learning algorithms can identify factors that contribute to student success. This information can then be used by universities to develop more effective programs and support services that can help students achieve their academic goals.

More efficient resource allocation: Machine learning can help universities optimize the allocation of resources such as funding, faculty, and infrastructure. By analyzing data on program popularity, student demand, and other relevant factors, machine learning algorithms can help universities make informed decisions on resource allocation, ensuring that resources are being used effectively and efficiently.

**Enhanced program development:** Machine learning can help universities identify emerging trends and opportunities in the academic landscape. By analyzing data on industry demand, job market trends, and emerging technologies, machine learning algorithms can help universities develop new programs that are relevant to current and future needs.

**Improved decision-making**: Machine learning algorithms can analyze vast amounts of data quickly and accurately, providing university administrators with insights and recommendations that can inform decision-making. This can help universities make more informed decisions, reduce the risk of errors, and improve the overall effectiveness of their operations.

Overall, the use of machine learning in university decision making can help universities operate more efficiently and effectively, and ultimately, provide students with a better education and experience.

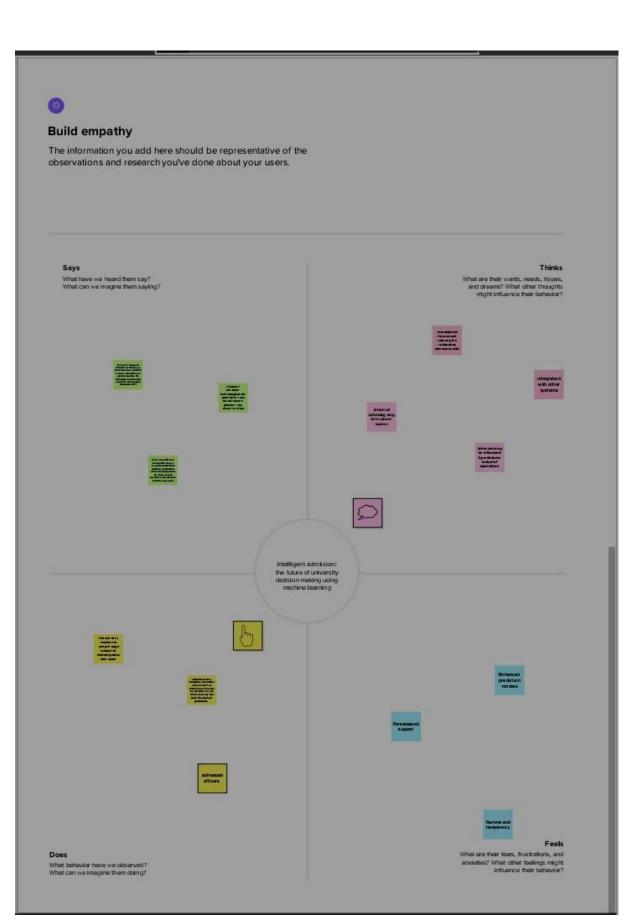


# **Empathy map**

Use this framework to develop a deep, shared understanding and empathy for other people. An empathy map helps describe the aspects of a user's experience, needs and pain points, to quickly understand your users' experience and mindset.

#### **Ideation Phase**

Date	16.03.2023
Team id and team members	*Lavanya *thingalarasi *gomathi *abinaya
Title	intellegent admissions:the future of university decision making with machine learning





# Brainstorm & idea prioritization

Use this template in your own brainstorming sessions so your team can unleash their imagination and start shaping concepts even if you're not sitting in the same room.

- ( ) 10 minutes to prepare
- 1 hour to collaborate
- 2-8 people recommended

#### ideation phase

Date	16.03.2023
Team id and team members	NM2023TMID24528 *Lavanya u *Thingalarasi u *Gomathi *Abinaya
Title	intellegent admissions:the future of university decision making with machine learning



# Before you collaborate

A little bit of preparation goes a long way with this session. Here's what you need to do to get going.

① 10 minutes

#### A Team gathering

Define who should participate in the session and send an invite. Share relevant information or pre-work ahead.

- B Set the goal
  - Think about the problem you'll be focusing on solving in the brainstorming session.
- Learn how to use the facilitation tools
  Use the Facilitation Superpowers to run a happy and productive session.

Open article -





#### Group ideas

Take turns sharing your ideas while clustering similar or related notes as you go. Once all sticky notes have been grouped, give each cluster a sentence-like label. If a cluster is bigger than six sticky notes, try and see if you and break it up into smaller sub-groups.

① 20 minutes

Develop predictive modes that can analyze past admissions data and identify patterns that are predictive of academic success. These modes could be used to identify the most promising andidates for admission.

Use machine &arning algorithms to screen applications for completeness and digibility. These algorithms out & identify common arrors and incomistencies in applications, and flag them for further review.

Use reschine learning aggettine to provide personalized recommendation to applicants based on their interest, academic background, and car our goals. This could help applicants make more informed decision about which programs to agic to and winth courses to take.

Use machine learning digorithms to help universifies make data-drive decisions about admissions places and procedures. For example, algorithms could analyze the effectiveness of different outreach programs and identify areas for improvement.

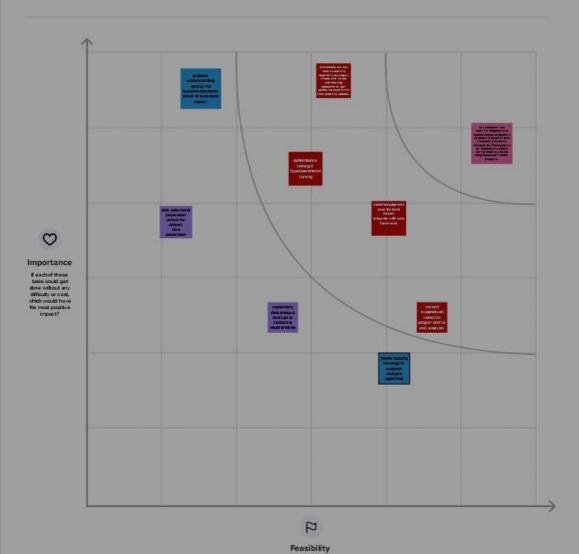
Use machine learning agorithms to help universities achieve diversity and inclusion goils. For example, algorithms could be used to identify can dictates from underrapresented groups who have the potential to succeed academically, but may not have the same opportunities as other



#### Prioritize

Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.

① 20 minutes



Regardlessof their importance, which tasks are more feasiblethan others? (Cost, time, effort, complexity, etc.)

#### After you collaborate

You can export the mural as an image or pdf to share with members of your company who might find it helpful.

#### Quick add-ons



#### Share the mural

**Share a view link** to the mural with stakeholders to keep them in the loop about the outcomes of the session.



#### Export the mural

Export a copy of the mural as a PNG or PDF to attach to emails, include in slides, or save in your crive.

#### Keep moving forward



#### Strategy blueprint

Define the components of a new idea or strategy.

Open the template →



#### Customer experience journey map

Understand customer needs, motivations, and obstacles for an experience.

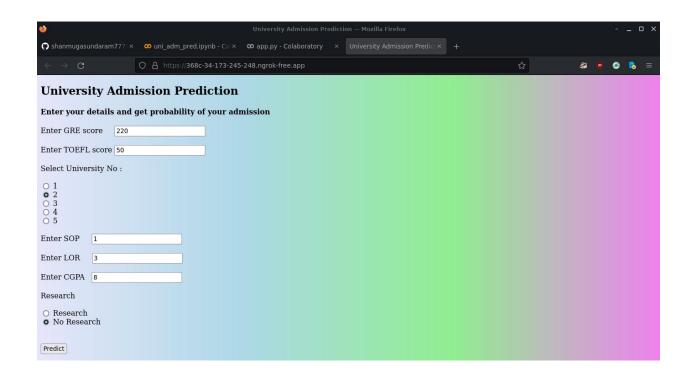
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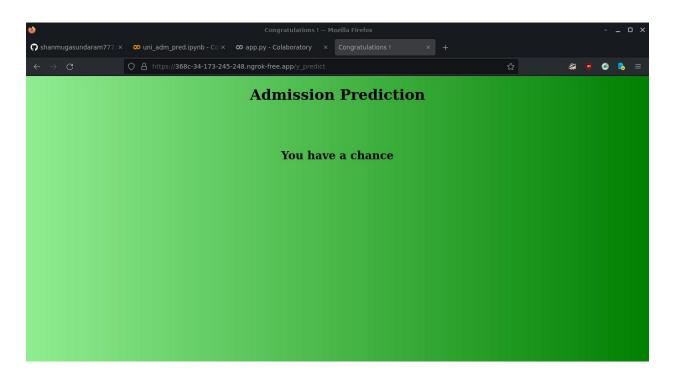


#### Strengths, weaknesses, opportunities & threats

Identify strengths, weaknesses, opportunities, and threats (SWOT) to develop a plan.

Open the template →





# **RESULT:**

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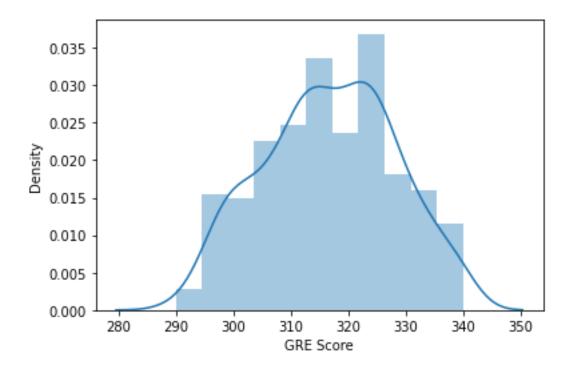
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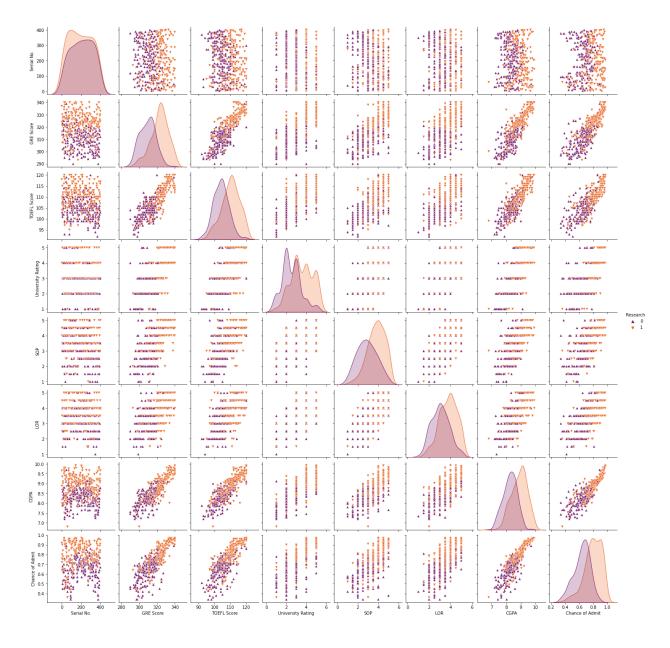
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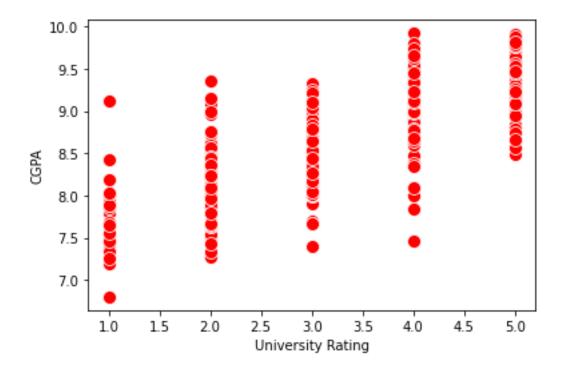
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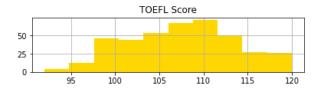


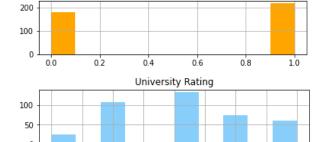






Research

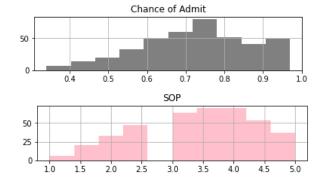




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[False, True], [True, False], [True, True], [False, True], [True, True], [False, True], [True, True], [True, True]) Model: "sequential"

dense (Dense) (None, 7) 56  dense_1 (Dense) (None, 7) 56	Layer (type)	Output Shape	Param #
dense_1 (Dense) (None, 7) 56	dense (Dense)	(None, 7)	56
	dense_1 (Dense)	(None, 7)	56
dense_2 (Dense) (None, 1) 8	dense_2 (Dense)	(None, 1)	8

Total params: 120
Trainable params: 120
Non-trainable params: 0

#### Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 7)	56
dense_1 (Dense)	(None, 7)	56
dense_2 (Dense)	(None, 1)	8

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Total params: 120 Trainable params: 120 Non-trainable params: 0

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16/16 [====================================	-] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 50/100	
16/16 [====================================	=] - 0s 2ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 51/100	
16/16 [====================================	=] - 0s 2ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 52/100	
16/16 [====================================	-] - 0s 2ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 53/100	3 0 0 / 1 0 0 000
16/16 [====================================	-] - 0s 2ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 54/100	1 0 2 / 1 (6020
16/16 [====================================	-] - Us 2ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 55/100	1 00 2 mg/stap 1000 6 6220 00000000 0 5656
16/16 [====================================	=] - 08 31118/8tep - 1088: 0.0239 - accuracy: 0.3030
Epoch 56/100 16/16 [====================================	-1 0s 2ms/stap 10ss: 6.6230 accuracy: 0.5656
Epoch 57/100	-] - 08 21116/step - 1088. 0.023) - decuracy. 0.3030
16/16 [====================================	-1 - 0s 2ms/sten - loss: 6 6239 - accuracy: 0 5656
Epoch 58/100	-] 05 21115/360p 1035. 0.0237 accuracy. 0.3030
16/16 [====================================	=1 - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 59/100	1
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 60/100	
16/16 [====================================	-] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 61/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 62/100	
16/16 [====================================	-] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 63/100	
16/16 [====================================	-] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 64/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 65/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 66/100	
16/16 [====================================	-] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 67/100	1 0 2 // 1 (6020
16/16 [====================================	-J - Us 3ms/step - 10ss: 6.6239 - accuracy: 0.5656
Epoch 68/100	

16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 69/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 70/100	•
-	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 71/100	-j 03 31113/3tep 1033. 0.023/ decuracy. 0.3030
*	1 0-2
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 72/100	
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 73/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 74/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 75/100	
*	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 76/100	1
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 77/100	-j 03 31113/3tep 1033. 0.023/ decuracy. 0.3030
-	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
	-1 - 08 3118/step - 1088. 0.0239 - accuracy. 0.3030
Epoch 78/100	1 0 2 / 1 (600)
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 79/100	
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 80/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 81/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 82/100	
-	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 83/100	1 os emanscep 10001 oto200
-	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 84/100	-j 03 31113/3tep 1033. 0.023/ decuracy. 0.3030
	-1 Oc 2mg/stan loss: 6 6220 acquiracy: 0 5656
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 85/100	1 0 0 / 1 0 0000
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 86/100	
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 87/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 88/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 89/100	
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 90/100	1 00 0-1-10 Per 1-10
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 91/100	-j 03 3113/3tcp 1033. 0.0237 decuracy. 0.3030
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
-	-1 - 08 31118/8tep - 1088. 0.0239 - accuracy. 0.3030
Epoch 92/100	1 0 2 / 4 1 6 6220
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 93/100	
	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 94/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 95/100	
16/16 [====================================	=] - 0s 3ms/step - loss: 6.6239 - accuracy: 0.5656
Epoch 96/10	-
1	

# **ADVANTAGES:**

**Data analysis**: Machine learning algorithms can process large amounts of data quickly and accurately, providing insights into patterns and trends that may not be apparent through manual analysis.

**Predictive modeling**: By using historical data, machine learning algorithms can create predictive models that help universities anticipate future trends and outcomes.

**Efficiency**: By automating data analysis and decision-making processes, universities can save time and resources, allowing for more efficient operations.

**Improved decision-making**: Machine learning algorithms can help universities make data-driven decisions, reducing the risk of errors and improving overall effectiveness.

**Resource allocation**: Machine learning can help universities optimize the allocation of resources such as funding, faculty, and infrastructure.

**Student success**: By identifying factors that contribute to student success, universities can develop more effective programs and support services that better meet the needs of their students.

**Program development**: Machine learning can help universities identify emerging trends and opportunities, allowing them to develop new programs that are relevant and valuable to students.

# **DISADVANTAGES:**

**Bias**: Machine learning algorithms can be biased if the data used to train them is not representative of the entire population or if the algorithms themselves contain inherent biases.

**Interpretability**: Machine learning algorithms can be difficult to interpret, making it challenging to understand how decisions are being made or to detect errors.

**Privacy concerns**: Collecting and analyzing large amounts of student data may raise concerns about privacy and security.

**Dependence on technology**: Overreliance on machine learning algorithms may lead to a loss of critical thinking and decision-making skills among university administrators.

**Cost**: Implementing a machine learning system may require significant financial investment, which may not be feasible for all universities.

**Technical expertise**: Developing and implementing a machine learning system requires specialized technical knowledge, which may be difficult to acquire or maintain.

**Ethical considerations**: Using machine learning in decision making requires careful consideration of ethical concerns, such as fairness, transparency, and accountability.

university decision making, it is important to carefully consider the Potential risks and drawbacks and to ensure that ethical considerations and privacy concerns are addressed.

# **APPLICATION:**

Intelligent admission using machine learning has the potential to revolutionize university decision making processes . here are some potential applications:

- 1.PREDECTIVE MODELING: machine learning algorithm can analyze vast amounts of data to identify patterns and make predictions about which students are likely to be successful in their studies.this could help universities make more informed decisions about which applicants to admit, and also help identify students who may be at risk of droping out or under performing.
- **2.PERSONALIZED RECOMMENDATIONS**: by analyzing data about a students academic performance, extra curicular activities, and other factors, machine learning algorithm can provide personalized recommendations to students about which programs or cources they should consider .this could

help students make more informed decision about their academic paths and increase their chances of success.

**3.AUTOMATED ESSAY GRADING**:machine learning algorithms can be trained to automatically grade essays and other written assignments, reducing the workload for admissions officers and providing more consistent grading across all applicants.

4.FRAUD DETECTION:machine learning algorithms can be used to detect fraud in applications, such as student to submit false transcripts or letters of recommendations.

# **Conclusion:**

In conclusion, the use of machine learning in university decision making has the potential to provide significant benefits in higher education, including more efficient operations, improved student outcomes, and enhanced innovation. By analyzing large amounts of data and developing predictive models, machine learning algorithms can help universities make data-driven decisions that are more accurate and effective. However, it is important to carefully consider the potential risks and drawbacks of using machine learning in university decision making, such as bias, interpretability issues, privacy concerns, and dependence on technology. Ethical considerations should also be taken into account, such as fairness, transparency, and accountability. Overall, the application of machine learning in university decision making requires careful consideration of the potential benefits and risks, as well as a commitment to ethical and responsible use of the technology.

# THE FUTURE SCOPE:

The future scope of using machine learning in university decision making is vast and promising. As the field of machine learning continues to advance, universities can expect to see even greater benefits in a variety of areas, including:

**Personalized learning**: Machine learning algorithms can help universities develop personalized learning experiences tailored to individual student needs and preferences.

**Continuous improvement**: By analyzing data on student outcomes, universities can use machine learning to continuously improve programs and support services.

**Resource optimization**: Machine learning can help universities optimize the allocation of resources such as funding, faculty, and infrastructure, leading to more efficient and effective operations.

**Real-time decision-making**: As machine learning algorithms become more sophisticated, universities may be able to make real-time decisions based on live data feeds, allowing for more agile and responsive decision-making.

**Collaboration and innovation**: By using machine learning to identify emerging trends and opportunities, universities can foster collaboration and innovation across disciplines and departments.

# **APPENDIX:**

#### **INDEX.html**:

```
<!DOCTYPE html>
<html>
<head>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <title>University Admission Prediction</title>
    <style type="text/css">
        body{
            background-image: linear-gradient(to right, lavender, lightblue,
lightgreen, violet);
        }
    </style>
</head>
<body>
    <h2>University Admission Prediction</h2>
    <h4>Enter your details and get probability of your admission</h4>
    <form method="post" action="{{url_for('y_predict')}}">
        <label for="gre">Enter GRE score &emsp; </label>
        <input type="text" name="gre" required> <br> <br>
        <label for="toefl">Enter TOEFL score </label>
        <input type="text" name="toefl" required> <br> <br>
        Select University No : <br>
        <input type="radio" name="uni num" value="1">
        <label for="1">1</label> <br>
        <input type="radio" name="uni_num" value="2">
        <label for="2">2</label> <br>
        <input type="radio" name="uni num" value="3">
        <label for="3">3</label> <br>
        <input type="radio" name="uni_num" value="4">
        <label for="4">4</label> <br>
        <input type="radio" name="uni num" value="5">
        <label for="5">5</label> <br> <br>
        <label for="sop">Enter SOP &emsp; </label>
        <input type="text" name="sop" required> <br>     <br>
        <label for="lor">Enter LOR &emsp; </label>
        <input type="text" name="lor" required> <br> <br>
```

# **Predict:**

```
<!DOCTYPE html>
<html>
<head>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <title>Sorry</title>
    <style type="text/css">
       body{
           background-image: linear-gradient(to right, tomato, red);
       }
    </style>
</head>
<body>
    <center>
    <h1>Admission Prediction</h1>
    <h2>You do not have a chance</h2>
    </center>
</body>
</html>
```

```
<!DOCTYPE html>
<html>
<head>
    <meta charset="utf-8">
   <meta name="viewport" content="width=device-width, initial-scale=1">
   <title>Congratulations !</title>
   <style type="text/css">
       body{
           background-image: linear-gradient(to right, lightgreen, green);
       }
   </style>
</head>
<body>
   <center>
    <h1>Admission Prediction</h1>
   <h2>You have a chance</h2>
   </center>
</body>
</html>
```