

A REVIEW OF LIVER PATIENT ANALYSIS METHODS USING MACHINE LEARNING

CONTENTS

CONTENTS OF TABLES

1.INTRODUCTION

INTRODUCTION

Liver patient analysis using machine learning is an emerging field of research that aims to develop effective diagnostic and prognostic tools for liver disease. Machine learning techniques enable the analysis of large datasets of patient information, such as medical history, clinical examination results, laboratory tests, and imaging studies, to identify patterns and correlations that may be indicative of liver disease.

There are several methods of liver patient analysis using machine learning, including supervised learning, unsupervised learning, and deep learning. Supervised learning algorithms are trained on labeled data to predict outcomes, such as liver disease diagnosis or prognosis. Unsupervised learning algorithms, on the other hand, are used

to identify patterns and clusters within the data without prior knowledge of the outcomes. Deep learning is a subset of machine learning that uses artificial neural networks to model complex relationships between variables.

Liver patient analysis using machine learning has the potential to improve the accuracy and efficiency of liver disease diagnosis and treatment. By analyzing large amounts of patient data, machine learning algorithms can identify early signs of liver disease, predict disease progression, and personalize treatment plans based on individual patient characteristics.

However, it is important to note that machine learning models are only as good as the data they are trained on. Therefore, the quality and representativeness of the data used for analysis are critical factors in the success of these methods. Additionally, the interpretability of machine learning models is an ongoing challenge, as their decision-making processes can be difficult to understand and explain to clinicians and patients.

1.1 OVERVIEW

Liver patient analysis using machine learning involves the use of various computational techniques to analyze large datasets of patient information in order to identify patterns and relationships that

may be indicative of liver disease. The main methods of liver patient analysis using machine learning include:

1. **Supervised Learning:** This involves training machine learning models on labeled data to predict liver disease diagnosis or prognosis. Examples of supervised learning techniques that can be used for liver patient analysis include logistic regression, decision trees, and random forests.
2. **Unsupervised Learning:** This involves identifying patterns and clusters within the data without prior knowledge of the outcomes. Examples of unsupervised learning techniques that can be used for liver patient analysis include clustering, principal component analysis (PCA), and independent component analysis (ICA).
3. **Deep Learning:** This is a subset of machine learning that uses artificial neural networks to model complex relationships between variables. Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been used for liver patient analysis tasks such as liver disease detection, classification, and segmentation.
4. **Feature Selection:** This involves selecting the most relevant features (i.e., patient characteristics, clinical data, or imaging features) for the analysis. Feature selection techniques, such as recursive feature elimination and principal component analysis, can be used to reduce the dimensionality of the data and improve the accuracy of the analysis.
5. **Transfer Learning:** This involves leveraging pre-trained models to improve the performance of the analysis on a new dataset. Transfer learning techniques can be used for tasks such as liver disease classification and segmentation.

Overall, the use of machine learning methods for liver patient analysis has the potential to improve the accuracy and efficiency of liver disease diagnosis, prognosis, and treatment. However, the quality and representativeness of the data used for analysis are critical factors in the success of these methods. Additionally, the interpretability of machine learning models remains an ongoing challenge in this field.

1.2 PURPOSE

The purpose of liver patient analysis using machine learning is to improve the accuracy, efficiency, and personalization of liver disease diagnosis, prognosis, and treatment. Machine learning algorithms can analyze large datasets of patient

information, such as medical history, laboratory tests, imaging studies, and genetic data, to identify patterns and correlations that may be indicative of liver disease. The ultimate goal is to provide clinicians with tools that can aid in early detection, accurate diagnosis, personalized treatment planning, and monitoring of liver disease progression.

Some specific purposes of liver patient analysis using machine learning include:

1. **Early Detection:** Machine learning algorithms can analyze large amounts of patient data to identify early signs of liver disease, which can lead to earlier intervention and better outcomes.
2. **Accurate Diagnosis:** Machine learning models can aid in accurate diagnosis of liver disease by combining multiple sources of data and detecting subtle patterns that may not be visible to human observers.
3. **Personalized Treatment Planning:** By analyzing patient data, machine learning algorithms can help identify the most effective treatments for individual patients based on their unique characteristics, such as disease stage, comorbidities, and genetic makeup.
4. **Monitoring Disease Progression:** Machine learning algorithms can analyze patient data over time to monitor disease progression and predict future outcomes, allowing for timely intervention and personalized treatment adjustments.

Overall, the purpose of liver patient analysis using machine learning is to provide clinicians with more accurate, efficient, and personalized tools for the diagnosis, treatment, and monitoring of liver disease.

2.PROBLEM DEFINITION & DESIGN THINKING

2.1 EMPATHY MAP

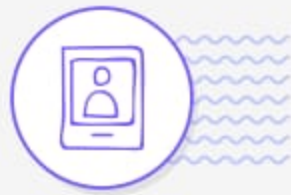
4:23

3.00 KB/S VoLTE 56%

← DOC-20230413-WA0006.



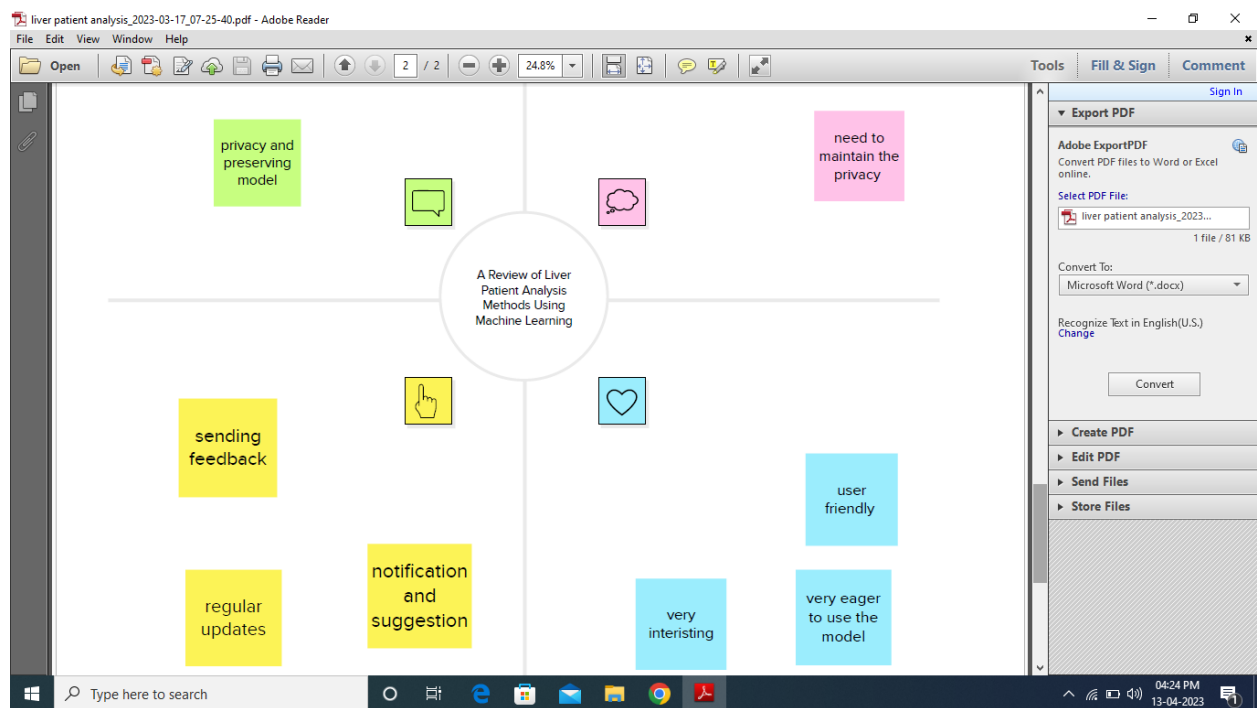
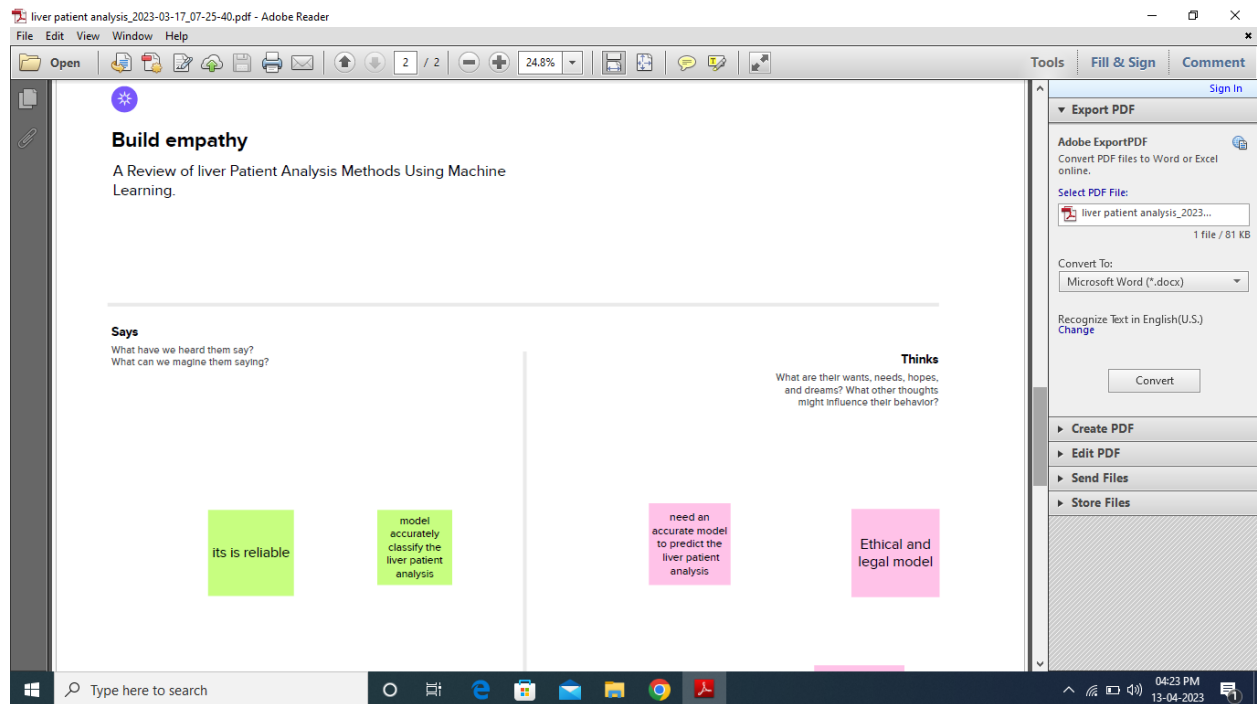
Template

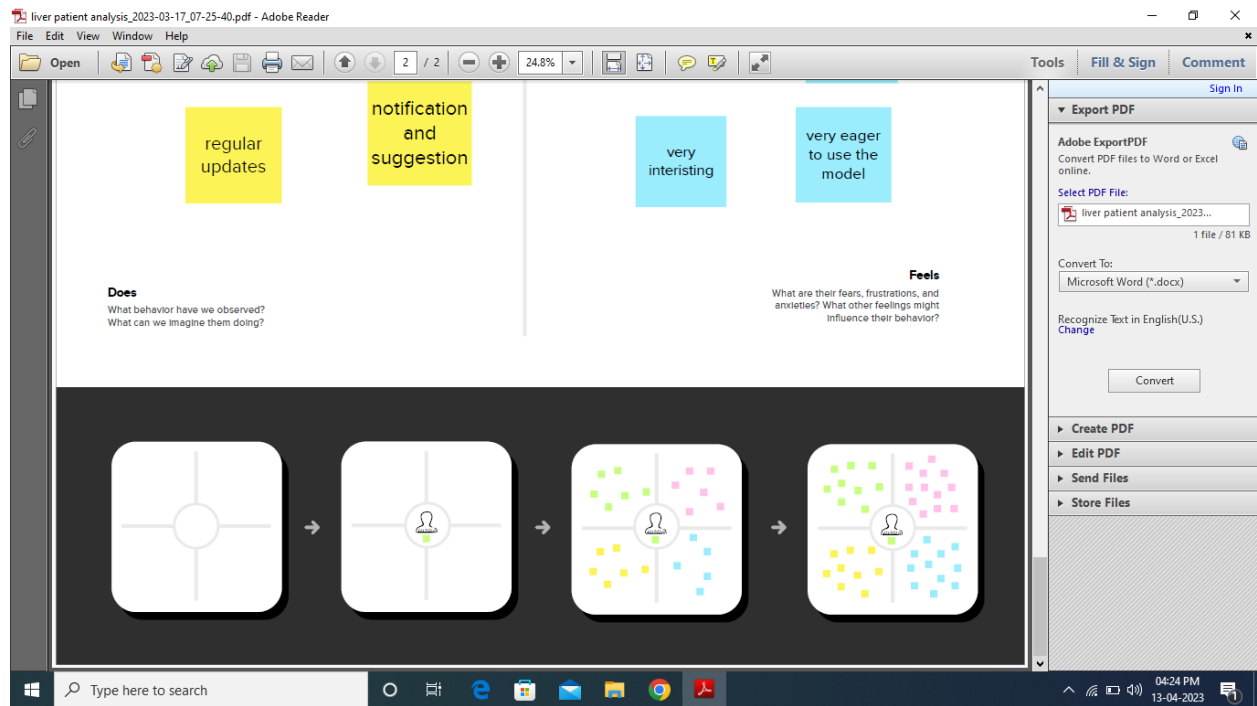


Empathy map

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.

DATE	16-3-2023
TEAM ID & TEAM MEMBERS	NW02023TR019743 1.CHANDHRI 2.MATHAN KUMAR 3.KARTHIKEYAN 4.NAVEEN KUMAR
PROJECT NAME	A review of Liver Patient Analysis Methods Using Machine Learning





2.2 IDEATION & BRAINSTORMING MAP

 [Share template feedback](#)



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.

 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.

C

Learn how to use the facilitation tools

Use the Facilitation Superpowers to run a happy and productive session.

[Open article](#)



1

Define your problem statement

What problem are you trying to solve? Frame your problem as a How Might We statement. This will be the focus of your brainstorm.

🕒 5 minutes

PROBLEM

A review of liver patient
analysis methods using machine
learning



Key rules of brainstorming

To run a smooth and productive session



Stay in topic.



Encourage wild ideas.



Defer judgment.



Listen to others.



Go for volume.



If possible, be visual.

1

Define your problem statement

What problem are you trying to solve? Frame your problem as a How Might We statement. This will be the focus of your brainstorm.

🕒 5 minutes

PROBLEM

A review of liver patient
analysis methods using machine
learning



Key rules of brainstorming

To run a smooth and productive session



Stay in topic.



Encourage wild ideas.



Defer judgment.



Listen to others.



Go for volume.



If possible, be visual.

2

Brainstorm

Write down any ideas that come to mind that address your problem statement.

🕒 10 minutes

Chandhru

Liver disease
is the leading
cause of
global death

Data
Collection

Model
Training

Handling
Missing
Values

Mathan kumar

Early
prediction of
liver disease
can reduce
the death rate

Data
preprocessing

Model
Testing

Identify the
individual
who are at
high risk

TIP



You can select a sticky note and hit the pencil [switch to sketch] icon to start drawing!

Karthikeyan

Machine Learning algorithm can be used to predict liver disease

Feature Selection

Reduce the burden of health care system

ANN Model

Naveen kumar

Model Selection

Health care professionals make reliable decisions

Logistic Regression

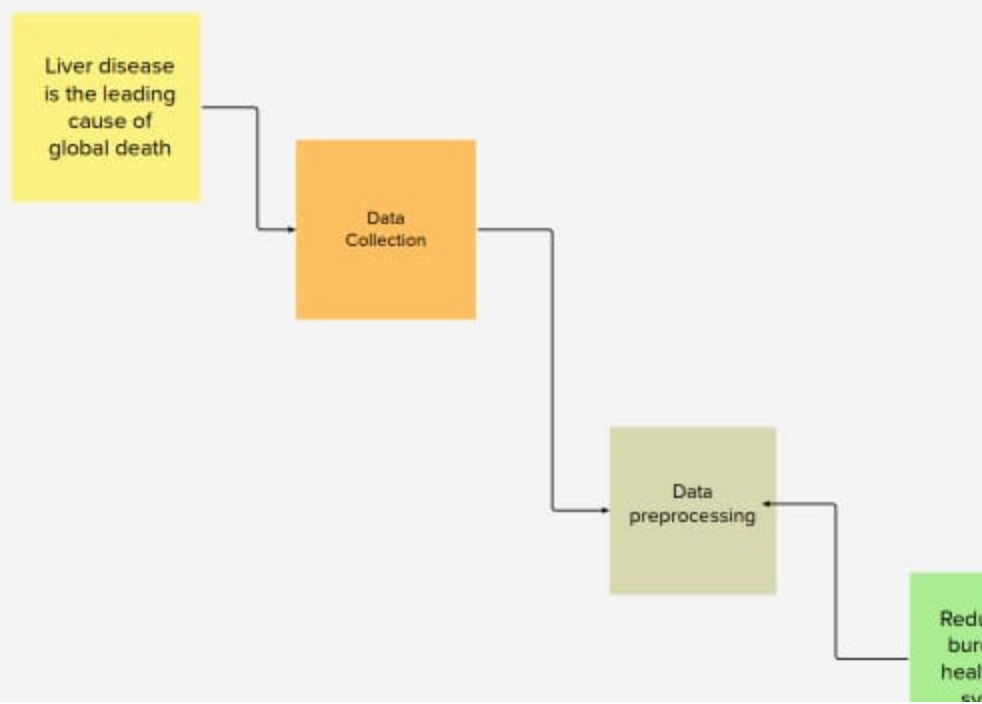
KNN Model

3

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 can break it up into smaller sub-groups.

🕒 20 minutes

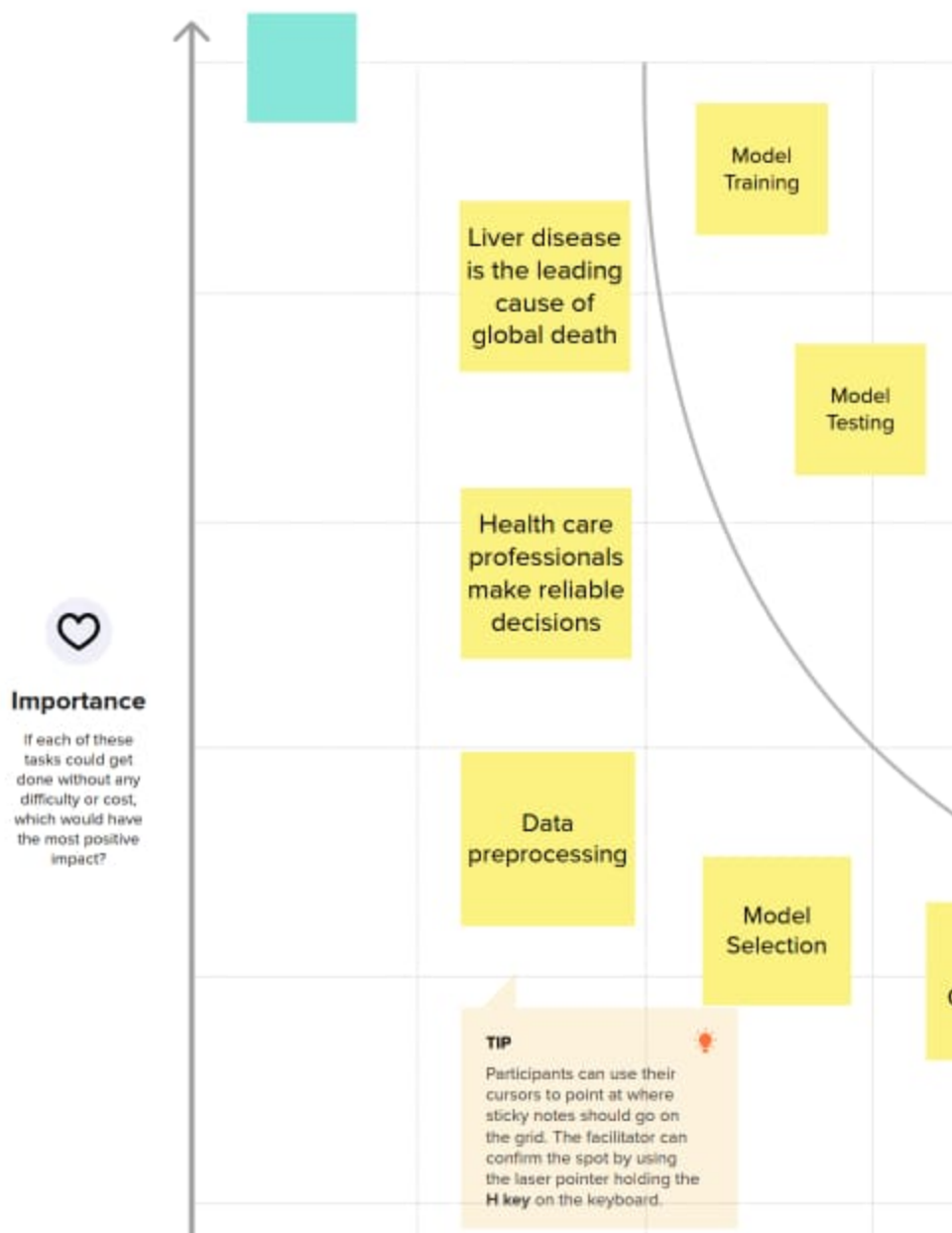


4

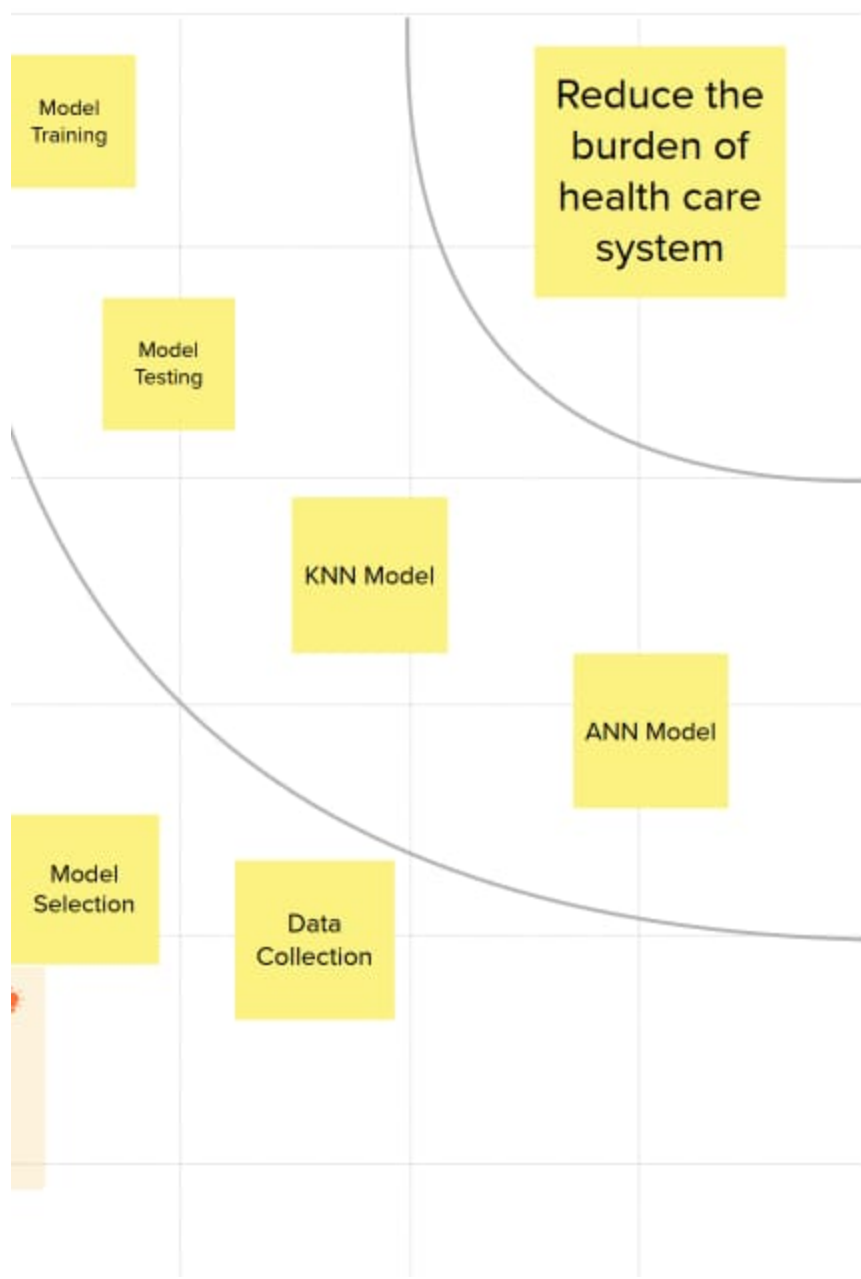
Prioritize

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.

🕒 20 minutes



t





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 drive.

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.

[Open the template →](#)



Strengths, weaknesses, opportunities & threats

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

[Open the template →](#)

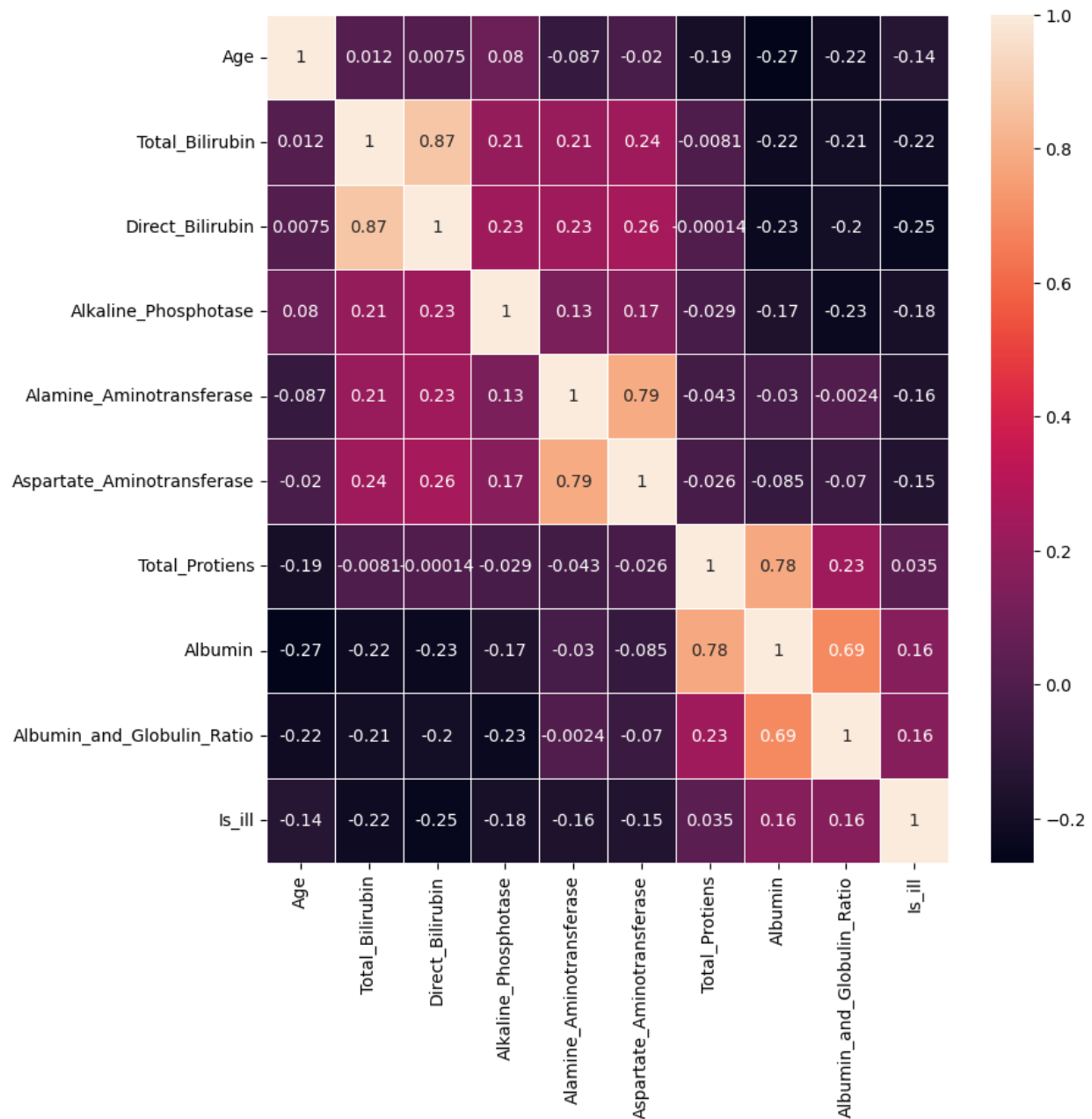


[Share template feedback](#)

3.RESULT

corr_matrix = df.corr()

<Axes: >



4.ADVANTAGES & DISADVANTAGES

ADVANTAGES & DISADVANTAGES

Advantages of liver patient analysis using machine learning:

1. **Improved Accuracy:** Machine learning algorithms can identify subtle patterns and relationships in large datasets that may not be immediately visible to humans, leading to more accurate diagnoses and treatment plans.
2. **Personalized Treatment:** Machine learning algorithms can analyze patient data to identify the most effective treatment plans for individual patients based on their unique characteristics.
3. **Early Detection:** Machine learning algorithms can analyze patient data to identify early signs of liver disease, allowing for earlier intervention and better outcomes.
4. **Efficiency:** Machine learning algorithms can analyze large amounts of patient data in a short amount of time, reducing the workload on clinicians and improving the efficiency of diagnosis and treatment planning.

Disadvantages of liver patient analysis using machine learning:

1. **Quality of Data:** The accuracy and reliability of machine learning algorithms depend on the quality and representativeness of the data used for training. If the data is biased or incomplete, the resulting algorithms may be inaccurate or unreliable.
2. **Interpretability:** Machine learning algorithms can be difficult to interpret and understand, making it challenging for clinicians to understand the reasoning behind the diagnosis or treatment plan.
3. **Overfitting:** Machine learning algorithms can sometimes overfit to the training data, resulting in poor performance when applied to new data.
4. **Ethical Issues:** Machine learning algorithms can potentially perpetuate or amplify biases that exist in the data used for training, leading to unethical or discriminatory outcomes.

Overall, the advantages of using machine learning in liver patient analysis outweigh the disadvantages, but it is important to address the limitations and challenges associated with these methods to ensure their effectiveness and ethical use in clinical practice.

5.APPLICATIONS

APPLICATIONS

There are various applications of machine learning in liver patient analysis. Some of the common applications include:

1. **Liver Disease Diagnosis:** Machine learning algorithms can be used to aid in the diagnosis of liver diseases such as hepatitis, cirrhosis, and liver cancer. These algorithms can analyze patient data such as medical history, laboratory tests, imaging studies, and genetic data to identify patterns and correlations that may be indicative of liver disease.
2. **Prognosis:** Machine learning algorithms can predict the progression and outcome of liver diseases based on patient data, allowing clinicians to identify patients who may require more aggressive treatment or closer monitoring.
3. **Treatment Planning:** Machine learning algorithms can help identify the most effective treatment plans for individual patients based on their unique characteristics, such as disease stage, comorbidities, and genetic makeup.
4. **Liver Transplantation:** Machine learning algorithms can assist in identifying the best candidates for liver transplantation and predicting outcomes after transplantation based on patient data.
5. **Drug Development:** Machine learning algorithms can aid in the development of new drugs for liver diseases by identifying potential drug targets and predicting the efficacy of new drugs based on patient data.
6. **Radiomics:** Machine learning algorithms can analyze medical images of the liver, such as computed tomography (CT) scans or magnetic resonance imaging (MRI) scans, to aid in diagnosis, prognosis, and treatment planning.

Overall, the applications of machine learning in liver patient analysis are diverse and offer potential benefits for improving the accuracy, efficiency, and personalization of liver disease diagnosis, prognosis, and treatment.

6.CONCLUSION

CONCLUSION

In conclusion, machine learning algorithms have the potential to revolutionize the diagnosis, prognosis, and treatment of liver diseases. By analyzing large amounts of patient data, these algorithms can identify subtle patterns and relationships that may not be visible to human observers, leading to more accurate and personalized diagnosis and treatment plans. While there are limitations and challenges associated with the use of machine learning in liver patient analysis, such as data quality and interpretability issues, the potential benefits outweigh the drawbacks.

Future research in this field will focus on improving the accuracy and reliability of machine learning algorithms, addressing ethical concerns and ensuring their ethical use, and integrating these algorithms into clinical practice to improve patient outcomes. With continued development and refinement, machine learning has the potential to transform the field of liver disease management, ultimately leading to better patient care and improved quality of life.

7.FUTURE SCOPE

FUTURE SCOPE

The future scope of liver patient analysis using machine learning is vast and promising. Some of the potential areas of development and application include:

1. **Integration into Clinical Practice:** Machine learning algorithms have the potential to transform the way liver diseases are diagnosed, prognosed, and treated. The integration of these algorithms into clinical practice will require further research and development to ensure their effectiveness and ethical use.
2. **Personalized Medicine:** Machine learning algorithms can analyze patient data to identify the most effective treatment plans for individual patients based on their unique characteristics, such as genetic makeup, lifestyle factors, and disease history. The future of liver patient analysis using machine learning will involve the development of more personalized treatment plans.
3. **Advanced Imaging Techniques:** Machine learning algorithms can analyze medical images of the liver, such as CT scans or MRI scans, to aid in diagnosis, prognosis, and treatment planning. The future scope of this area involves the development of more advanced imaging techniques that can provide even more detailed information about the liver.
4. **Big Data Analysis:** The volume of data generated in liver patient analysis is growing rapidly, and machine learning algorithms have the potential to analyze and extract insights from this data. The future scope of liver patient analysis using machine learning involves the development of more advanced algorithms that can handle larger and more complex datasets.
5. **Drug Development:** Machine learning algorithms can aid in the development of new drugs for liver diseases by identifying potential drug targets and predicting the efficacy of new drugs based on patient data. The future scope of this area involves the development of more effective drugs and the integration of machine learning into the drug development process.

Overall, the future scope of liver patient analysis using machine learning is vast and holds great potential for improving patient outcomes and transforming the field of liver disease management.

8.APPENDIX

SOURCE CODE

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import rcParams
from scipy import stats

data=pd.read_csv('/content/indian_liver_patient.csv')

data.head()

data.info()

data.isnull().any()

data.isnull().sum()

data["Albumin_and_Globulin_Ratio"].fillna(data["Albumin_and_Globulin_Ratio"].median(), inplace=True)

data.isnull().sum()

data.info()

from sklearn.preprocessing import LabelEncoder
lc = LabelEncoder()
data['Gender'] = lc.fit_transform(data['Gender'])

data.describe()

sns.distplot(data['Age'])
plt.title('Age Distribution Graph')
plt.show()

plt.figure(figsize=(10,7))
sns.heatmap(data.corr(),annot=True)

X=data.iloc[:, :-1]
```

```
y=data.Dataset

X

y

from sklearn.preprocessing import scale
X_scaled=pd.DataFrame(scale(X),columns=X.columns)

X_scaled.head()

from sklearn.model_selection import train_test_split
X_train, X_test,y_train,y_test =
train_test_split(X_scaled,y,test_size=0.2,random_state=42)

pip install imblearn

from imblearn.over_sampling import SMOTE
smote = SMOTE()

x_resample, y_resample = smote.fit_resample(X,y)

x_resample

y_resample

X.shape

y.shape

X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)

y_train_smote.value_counts()

X

from sklearn.metrics._plot.confusion_matrix import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
modell=RandomForestClassifier()
```

```

modell1.fit(X_train_smote, y_train_smote)
y_predict=modell1.predict(X_test)
rf=accuracy_score(y_test, y_predict)
rf
print(confusion_matrix(y_test,y_predict))
print(classification_report(y_test, y_predict))

from sklearn.metrics._plot.confusion_matrix import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
model4=DecisionTreeClassifier()
model4.fit(X_train_smote, y_train_smote)
y_predict=model4.predict(X_test)
dt=accuracy_score(y_test, y_predict)
dt
print(confusion_matrix(y_test,y_predict))
print(classification_report(y_test, y_predict))

from sklearn.metrics._plot.confusion_matrix import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
model2=KNeighborsClassifier()
model2.fit(X_train_smote, y_train_smote)
y_predict=model2.predict(X_test)
knn =accuracy_score(y_test, y_predict)
knn
print(confusion_matrix(y_test,y_predict))
print(classification_report(y_test, y_predict))

from sklearn.metrics._plot.confusion_matrix import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
model5=LogisticRegression()
model5.fit(X_train_smote, y_train_smote)
y_predict=model5.predict(X_test)
lr=accuracy_score(y_test, y_predict)
lr
print(confusion_matrix(y_test,y_predict))
print(classification_report(y_test, y_predict))

```

```

import tensorflow.keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

classifier = Sequential()

classifier.add(Dense(units=100, activation='relu', input_dim=10))

classifier.add(Dense(units=50, activation='relu'))

classifier.add(Dense(units=1, activation='sigmoid'))

classifier.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

model_history = classifier.fit(X_train, y_train, batch_size=100,
validation_split=0.2, epochs=50)

model4.predict([[50,1,1.2,0.8,150,70,80,7.2,3.4,0.8]])

model11.predict([[50,1,1.2,0.8,150,70,80,7.2,3.4,0.8]])

classifier.save("liver.h5")

y_pred=classifier.predict(X_test)

y_pred

y_pred = (y_pred > 0.5)

y_pred

def predict_exit(sample_value):
    sample_value = np.array(sample_value)
    sample_value = sample_value.reshape(1, -1)
    sample_value = scale(sample_value)
    return classifier.predict(sample_value)

sample_value = [[50,1,1.2,0.8,150,70,80,7.2,3.4,0.8]]
if predict_exit(sample_value)>0.5:

```

```
        print('Liver Patient')
    else:
        print('Healthy')

acc_smote = [['Knn',knn],
             ['RandomForest',rf],['DecisionTree',dt],['Logisregression',lr]]

Liverpatient_pred=pd.DataFrame(acc_smote, columns=['Classification
models', accuracy_score])

Liverpatient_pred

import joblib

joblib.dump(modell, 'ETC.pkl')
```