```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from sklearn.metrics import confusion_matrix
from sklearn.metrics import recall_score, precision_score, f1_score
# Load the CSV file into a Pandas DataFrame
df = pd.read_csv('machine_failure_cleaned.csv')
# Extract the features and target variable
features = df.iloc[:, :-1].values
target = df.iloc[:, -1].values
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)
# Normalize the features
X_{\text{train}} = (X_{\text{train}} - \text{np.mean}(X_{\text{train}}, \text{axis=0})) / \text{np.std}(X_{\text{train}}, \text{axis=0})
X_{\text{test}} = (X_{\text{test}} - \text{np.mean}(X_{\text{test}}, \text{axis=0})) / \text{np.std}(X_{\text{test}}, \text{axis=0})
#print(df)
#print(df.iloc[0,:])
Suggested code may be subject to a license | gyan99.in/artificial-intelligence/deep-learning-explained-basics-benefits-and-limitation/
# Create an ANN with 3 layers
model = Sequential()
# First layer with 6 neurons
model.add(Dense(units=6, activation='relu', input_shape=(X_train.shape[1],)))
# Second layer with 4 neurons and a 0.2 dropout
model.add(Dense(units=4, activation='relu'))
model.add(Dropout(0.2))
# Last layer with 1 neuron and binary classification output
model.add(Dense(units=1, activation='sigmoid'))
# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
# Train the model
model.fit(X_train, y_train, epochs=100, batch_size=32)
# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print('Loss:', loss)
print('Accuracy:', accuracy)
```

https://colab.research.google.com/drive/1REPrEm7rge79PgL0y\_o74jWFdFMDZGjS#scrollTo=YZUEuLE-VnSF&printMode=true

```
Epoch 89/100
   246/246 [============ ] - 1s 5ms/step - loss: 0.0268 - accuracy: 0.9927
   Enoch 90/100
   Epoch 91/100
   Epoch 92/100
   246/246 [====
               Epoch 93/100
   246/246 [=============] - 1s 4ms/step - loss: 0.0260 - accuracy: 0.9934
   Epoch 94/100
   246/246 [====
                Enoch 95/100
   Epoch 96/100
   246/246 [====
              Epoch 97/100
   246/246 [============ ] - 2s 10ms/step - loss: 0.0248 - accuracy: 0.9936
   Epoch 98/100
   246/246 [====
               Epoch 99/100
   Epoch 100/100
   Loss: 0.004784504882991314
   Accuracy: 0.9994905591011047
# Predict the labels for the test set
y_pred = model.predict(X_test)
# Convert the predictions to binary values (0 or 1)
y_pred_binary = [int(round(p[0])) for p in y_pred]
# Get the confusion matrix
cm = confusion_matrix(y_test, y_pred_binary)
  62/62 [======= ] - 0s 5ms/step
# Calculate recall, precision and F score
recall = recall_score(y_test, y_pred_binary)
precision = precision_score(y_test, y_pred_binary)
f1 = f1_score(y_test, y_pred_binary)
# Print the confusion matrix with recall, precision and F score
print("Confusion Matrix:")
print(cm)
print("\nRecall:", recall)
print("Precision:", precision)
print("F1 Score:", f1)
print("\nThe confusion matrix shows that the model achieves very high precision recall, which is perfect.")
print("This shows that the model is extremely effective at correctly identifying both positive and negative cases with very low error.")
   Confusion Matrix:
   [[1911
   [ 1 51]]
   Recall: 0.9807692307692307
   Precision: 1.0
   F1 Score: 0.9902912621359222
   The confusion matrix shows that the model achieves very high precision recall, which is perfect.
```

This shows that the model is extremely effective at correctly identifying both positive and negative cases with very low error.