3-D PRINTER MATERIAL PREDICTION USING WATSON AUTO AI PROJECT

-RIYA SINHA

1) INDRODUCTION :

1.1 OVERVIEW

Artificial Intelligence (AI) is the leading field of science nowadays. Machines can learn and complete tasks independently. 3D printing is much more than the production of plastic prototypes. Additive manufacturing is the most prospective and highly evaluated technological field in the modern world.
Additive manufacturing is used to create objects with complex shapes which are not possible to manufacture with traditional techniques.
Various polymer, metal and bio materials are used in engineering applications mainly to create prototypes and finished products with unique shapes, multifunctional compositions, reliability and high quality. Digital manufacturing era just started, 9 ideas can be transported to the 3D models and then send directly to 3D printing machine that can start work and finish without human supervision. We predict one the basis of the most fundamental material properties is tensile strength, a material's resistance to breaking under tension.In conjunction with a sufficient ductility, tensile strength also indicates a material's toughness. Some materials break very sharply in a brittle failure, whereas more ductile ones, such as most plastics and metals, experience some deformation. To clearly understand this behavior, tensile strength data is commonly supplemented with a stress/strain curve. Materials of high tensile strength are typically found in structural, mechanical, or static components where a breakage is unacceptable, such as construction, automotive, aviation, as well as wires, ropes, bullet proof vests, and more. Today, 3D printing has progressed to the extent where it is able to deliver the same, or even higher tensile strength than traditional injection-molded plastics, such as polypropylene and ABS.

1.2 PURPOSE

To identify the type of material required after a 3D model is designed is a complicated task.The aim of the study is to determine the best material which will be perfect for the given use case. Where there are eleven setting parameters and one output parameters. Based on these input parameters we will predict the best material for model. This model will predict whether to use PLA or ABS. Hence, the selection of right material is important to get accurate 3D model.

2)LITERATURE SURVEY:

2.1 EXISTING PROBLEM & SOLUTION

1. Output/quality problems while 3D printing

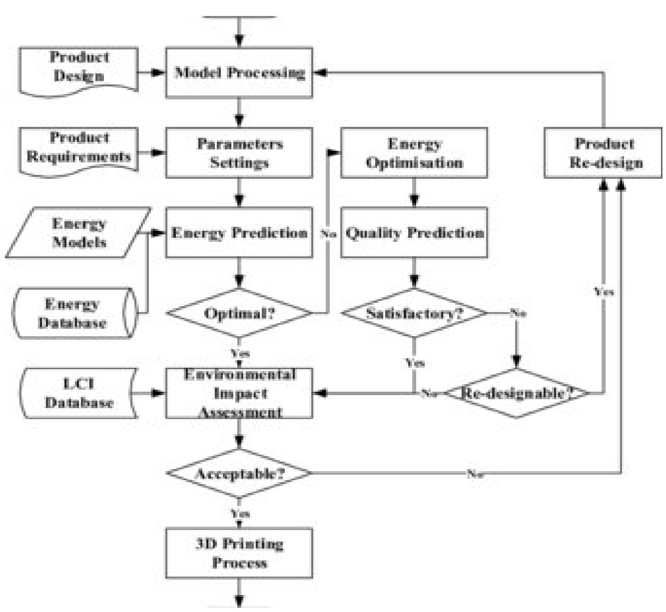
In some ways, this is the most basic thing, but there are many quality-related problems with 3D printing today:

- Fragile, delaminated FDM (fused deposition modeling) parts
- Low-resolution output
- Materials

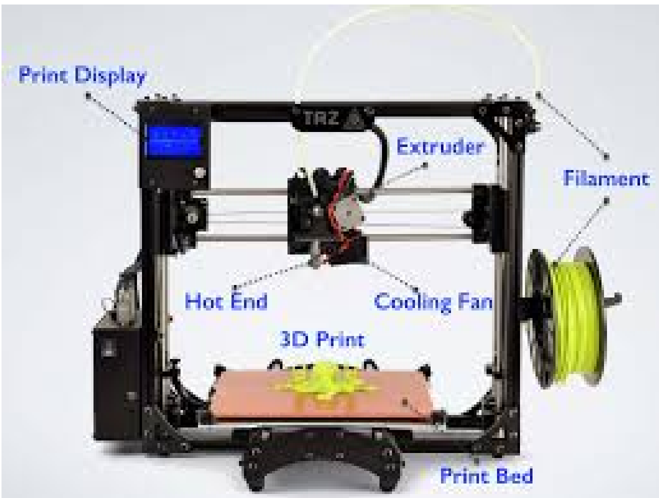
The materials are defined by what can be extruded, squirted, or melted, but this is not based on their application or final use. And even though there are some examples of multimaterials, it's typically only two at a time. So we're constraining ourselves.

3) THEORITICAL ANALYSIS:

3.1 BLOCK DIAGRAM



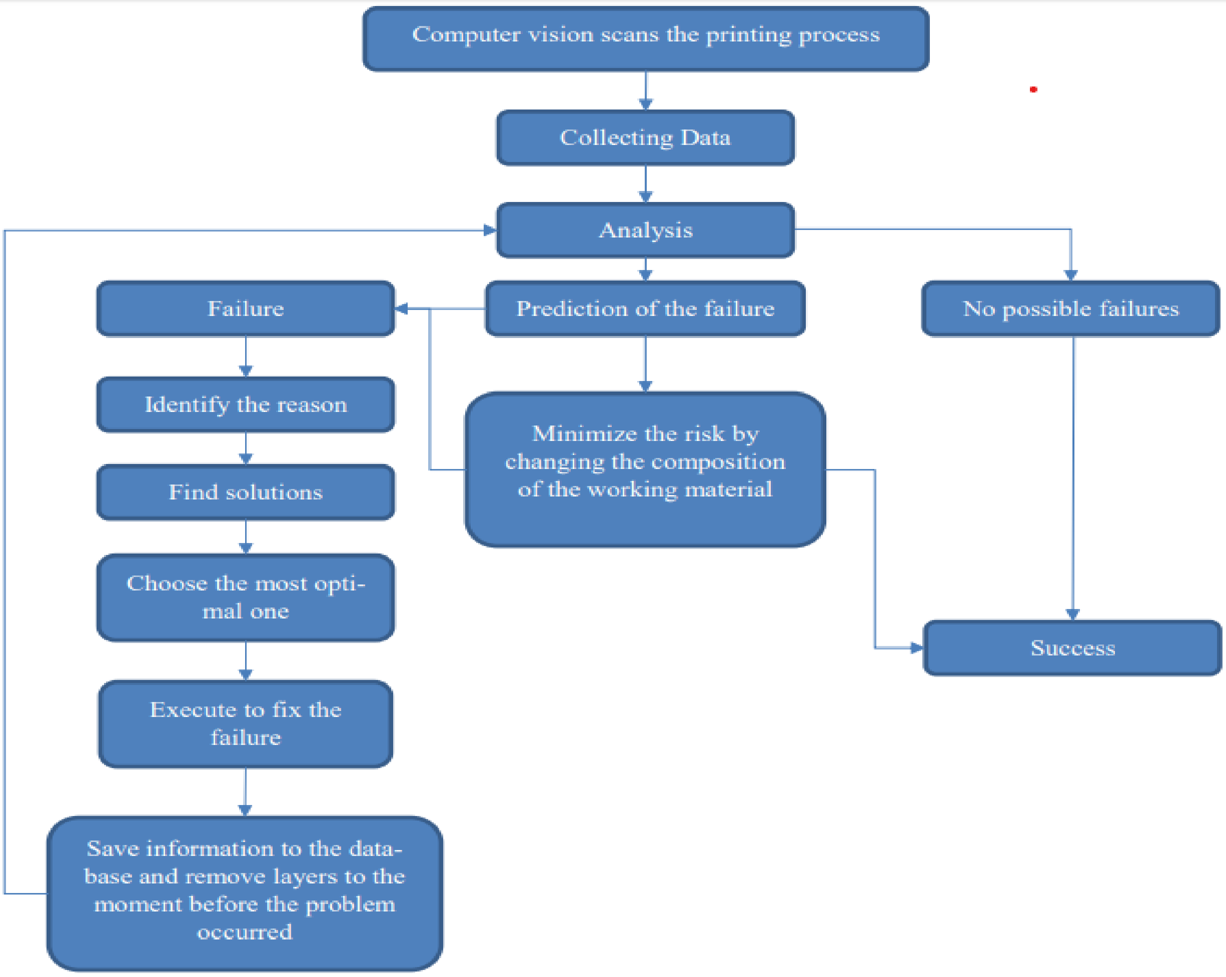
3.2 HARDWARE DESIGN



4) EXPERIMENTAL INVESTIGATIONS

High-performance polymers are plastics that have better thermal and mechanical properties than other engineering plastics. In general, polymers are relatively light materials when compared to metals. Currently, research era is focused on developing high-performance plastic such as PEEK (polyetheretherketone) for applications in drones, aircrafts, rockets and formula 1. This is due to its durability comparable to metal parts, its significant lightness and its capacity able to withstand operating temperatures of above 150 °C. However, these materials are well established and fabricated using conventional production method, which limits the freedom to achieve high-complexity structures. 3D printing or additive manufacturing techniques allow for complex shapes to be easily produced together with a degree of control over the process parameters. Though fused deposition modelling was attempted earlier with these polymers, more promising approaches such as robot-based extrusion method attained very little attention. In particular, 3D printing mould structures using high-performance materials for automated fibre placement (AFP) process need sufficient attention. This paper attempts experimental investigations with PEEK, using the robotic extrusion method. Thus, the thermal, mechanism of material consolidation, the effects of significant process parameters on critical responses and thermomechanical properties are determined with respect to its application for moulds for AFP process.

5) FLOWCHART



6) RESULT

The output of this prediction was 1 which is referred to PLA. Therefore PLA is better option as compared to ABS. Its ease of use and minimal warping issues make PLA filaments the perfect starting point for 3D printing. PLA is also one of the most environmentally-friendly 3D printing materials and, unlike ABS, is biodegradable. Among other PLA advantages are also its low cost and a wide assortment of colours and blends. However, the brittleness of the material makes PLA more suitable for non-functional prototyping, decorative and low-stress applications.

7)ADVANTAGES & DISADVANTAGES

ADVANTAGES

1. Improved shape
2. Good quality
3. Proper functioning of the 3D model
4. accuracy level is high
5. Time saving

DISADVANTAGES

1. Quality of material used on material wont be durable.
2. All eleven input parameters must be verified to get the best model.
3. Model wont function properly if right material not used.

8)APPLICATIONS

-Aerospace and defence: for functional prototype
-Industrial goods: modeling for on the spot demand
-Medical & Dental: 3D printing can be used to provide patient-specific solutions, such as implants and dental appliances.

9)CONCLUSION

_The main perspective way of artificial intelligence implementation in the world of additive manufacturing technologies is based on the 3D printing process development and bringing the design process to the new level.Machine learning improves the printing quality reducing risks of failure and manufacturing waste. The recycling in the field of additive manufacturing should be minimized with zero waste production. Also, there are a lot of possible ways which can be developed to protect the printing data and digital security system due to AI technologies.

Based on the model builts we conclude

- ABS and PLA are the most common desktop FDM printed materials and are typically similar in cost. ABS has superior mechanical properties but is harder to print with compared to PLA.
- PLA is ideal for 3D prints where aesthetics are important. Due to its lower printing temperature is easier to print with and therefore better suited for parts with fine details.
- ABS is best suited for applications where strength, ductility, machinability and

thermal stability are required. ABS is more prone to warping.

10) FUTURE SCOPE

The nearest future of the interaction between the artificial intelligence and additive manufacturing depends on the machine learning development. Elements of mechanisms and tools should be 3D printed and transported to substitute failed parts that will lead to the 76 reduction of spare parts costs and transportation expenses, and improved customer experience . The importance of this study is valuable for the future development of AM technologies, especially SLA 3D printing. This thesis covers all parts of possible cooperation of AM and AI system with detailed instructions. The AI system with computer vision can be easily developed based on the presented solutions.

11) BIBILOGRAPHY

https://www.twi-global.com/technical-knowledge/faqs/what-is-3d-printing/pros-and-cons

Autoshift.com -> redshift

12) APPENDIX

A.SOUCE CODE

```
import pandas as pd
data = pd.read_csv("data.csv", sep = ";")
```

In [3]:

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 12 columns):
layer_height        50 non-null float64
wall_thickness      50 non-null int64
infill_density      50 non-null int64
infill_pattern      50 non-null object
```

nozzle_temperature   50 non-null int64
bed_temperature   50 non-null int64
print_speed   50 non-null int64
material   50 non-null object
fan_speed   50 non-null int64
roughness   50 non-null int64
tension_strenght   50 non-null int64
elongation   50 non-null float64
dtypes: float64(2), int64(8), object(2)
memory usage: 4.8+ KB

Let's multiply these columns by 100 to make them more understandable.

In [4]:

```
data.layer_height = data.layer_height*100
data.elongation = data.elongation*100
```

In [5]:

```
data.head()
```

Out[5]:

	layer_height	wall_thickness	infill_density	infill_pattern	nozzle_temperature	bed_temperature	print_speed	material	fan_speed	roughness	tension_strenght	elongation
0	2.0	8	90	grid	220	60	40	abs	0	25	18	120.0
1	2.0	7	90	honeycomb	225	65	40	abs	25	32	16	140.0
2	2.0	1	80	grid	230	70	40	abs	50	40	8	80.0
3	2.0	4	70	honeycomb	240	75	40	abs	75	68	10	50.0
4	2.0	6	90	grid	250	80	40	abs	100	92	5	70.0

In this data set, ABS and PLA assigned 0 and 1 values for materials.

In [6]:

```
data.material = [0 if each == "abs" else 1 for each in data.material]
# abs = 0, pla = 1
```

```python
data.infill_pattern = [0 if each == "grid" else 1 for each in data.infill_pattern]
# grid = 0, honeycomb = 1
```

In [7]:

```python
data.head()
```

Out[7]:

	layer_height	wall_thickness	infill_density	infill_pattern	nozzle_temperature	bed_temperature	print_speed	material	fan_speed	roughness	tension_strenght	elongation
0	2.0	8	90	0	220	60	40	0	0	25	18	120.0
1	2.0	7	90	1	225	65	40	0	25	32	16	140.0
2	2.0	1	80	0	230	70	40	0	50	40	8	80.0
3	2.0	4	70	1	240	75	40	0	75	68	10	50.0
4	2.0	6	90	0	250	80	40	0	100	92	5	70.0

Seperate Input parameters and Prediction Materials.

In [18]:

```python
y_data = data.material.values
x_data = data.drop(["material"],axis=1)
```

In [19]:

```python
absm = data[data.material == 0]
pla = data[data.material == 1]
```

In [20]:

```python
absm.head()
```

Out[20]:

	layer_height	wall_thickness	infill_density	infill_pattern	nozzle_temperature	bed_temperature	print_speed	material	fan_speed	roughness	tension_strenght	elongation
0	2.0	8	90	0	220	60	40	0	0	25	18	120.0
1	2.0	7	90	1	225	65	40	0	25	32	16	140.0
2	2.0	1	80	0	230	70	40	0	50	40	8	80.0

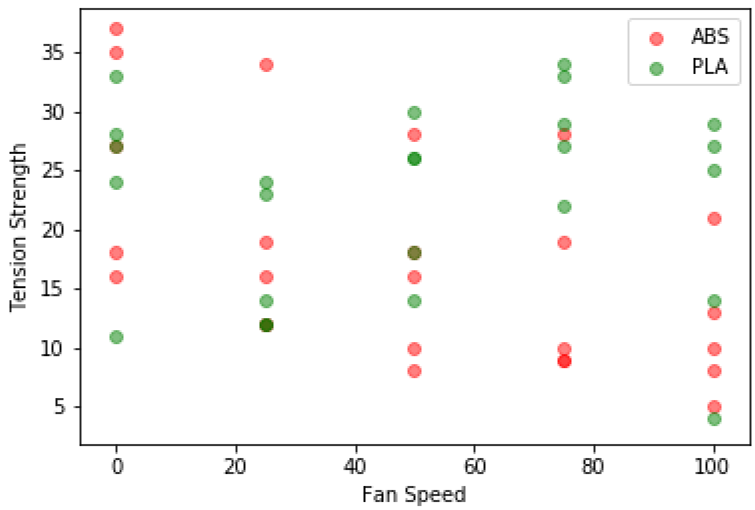
3	2.0	4	70	1	240	75	40	0	75	68	10	50.0
4	2.0	6	90	0	250	80	40	0	100	92	5	70.0

In [21]:

```
import matplotlib.pyplot as plt
```

In [22]:

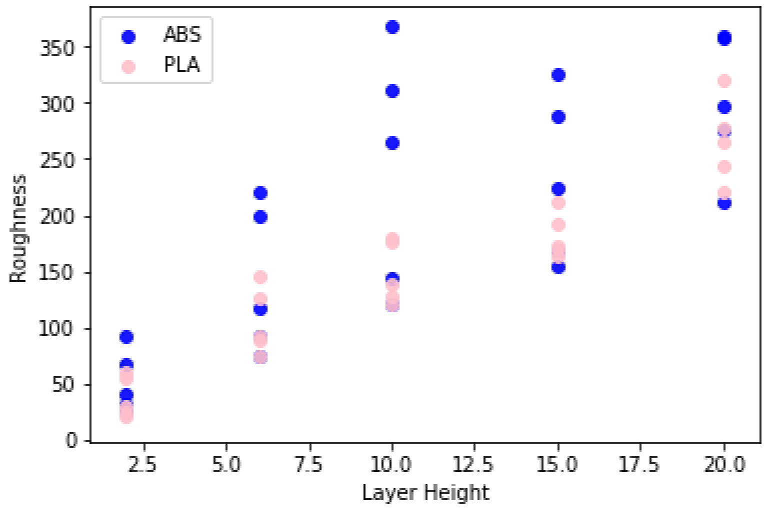
```
plt.scatter(absm.fan_speed,absm.tension_strenght,color="red",label="ABS",alpha= 0.5)
plt.scatter(pla.fan_speed,pla.tension_strenght,color="green",label="PLA",alpha= 0.5)
plt.xlabel("Fan Speed")
plt.ylabel("Tension Strength")
plt.legend()
plt.show()
```



As you see, the air circulation not good for ABS

In [23]:

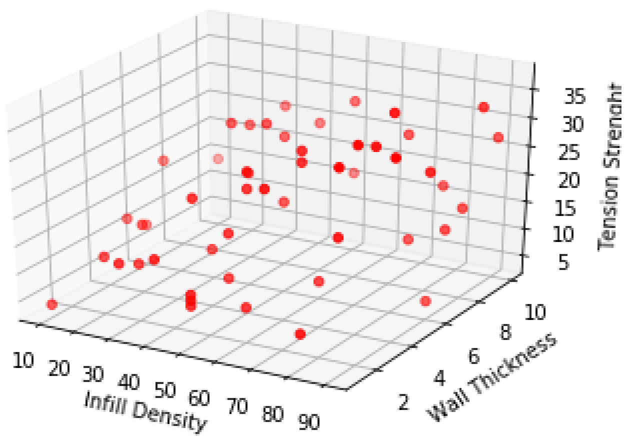
```
plt.scatter(absm.layer_height,absm.roughness,color="blue",label="ABS",alpha= 0.9)
plt.scatter(pla.layer_height,pla.roughness,color="pink",label="PLA",alpha= 0.9)
plt.xlabel("Layer Height")
plt.ylabel("Roughness")
plt.legend()
plt.show()
```



You can see as the layer height increases, the tensile strength increases. But PLA smoother than ABS

In [24]:

```
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt

fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

x = data.infill_density
y = data.wall_thickness
z = data.tension_strenght

ax.scatter(x, y, z, c='r', marker='o')

ax.set_xlabel('Infill Density')
ax.set_ylabel('Wall Thickness')
ax.set_zlabel('Tension Strenght')

plt.show()
```

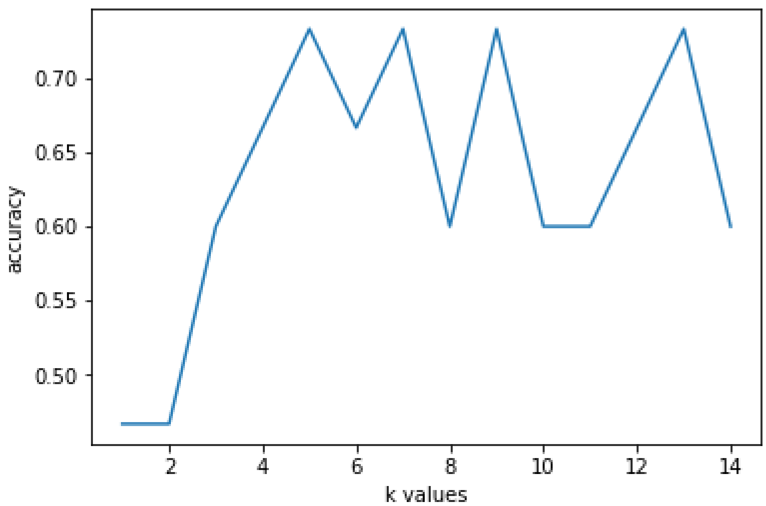


In [27]:

```
# normalization
x_norm = (x_data - np.min(x_data))/(np.max(x_data)-np.min(x_data))

# train test split
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x_norm,y_data,test_size = 0.3,random_state=1)

from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 3) # n_neighbors = k
knn.fit(x_train,y_train)
prediction = knn.predict(x_test)
print(" {} nn score: {} ".format(3,knn.score(x_test,y_test)))

score_list = []
for each in range(1,15):
    knn2 = KNeighborsClassifier(n_neighbors = each)
    knn2.fit(x_train,y_train)
    score_list.append(knn2.score(x_test,y_test))
    print(" {} nn score: {} ".format(each,knn2.score(x_test,y_test)))

plt.plot(range(1,15),score_list)
plt.xlabel("k values")
plt.ylabel("accuracy")
plt.show()
```

```
 3 nn score: 0.6
 1 nn score: 0.4666666666666667
 2 nn score: 0.4666666666666667
 3 nn score: 0.6
 4 nn score: 0.6666666666666666
```

5 nn score: 0.7333333333333333
6 nn score: 0.6666666666666666
7 nn score: 0.7333333333333333
8 nn score: 0.6
9 nn score: 0.7333333333333333
10 nn score: 0.6
11 nn score: 0.6
12 nn score: 0.6666666666666666
13 nn score: 0.7333333333333333
14 nn score: 0.6



In [ ]:

```
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation
from keras.layers import Input, Dense, Flatten
from keras.optimizers import SGD
from keras.layers.normalization import BatchNormalization

model = Sequential()
model.add(Dense(32,input_dim=11))
model.add(BatchNormalization(axis = -1))
model.add(Activation('relu'))
model.add(Dropout(0.25))
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.25))
model.add(Dense(16))
model.add(Activation('softmax'))
```

```
model.compile(optimizer='adam', loss = 'sparse_categorical_crossentropy', metrics=['accuracy'])
model.fit(x_data,y, epochs=500, batch_size =32, validation_split= 0.20)
```

In [ ]:

```
a1 = 4 #layer_height*100
a2 = 5 #wall_thickness
a3 = 60 #infill_density
a4 = 0 #infilkk_pattern
a5 = 232 #nozzle_temperature
a6 = 74 #bed_temperature
a7 = 90 #print_speed
a8 = 100 #fan_speed
a9 = 150 #roughness
a10 = 30 #tension_strenght
a11 = 200 #elangation*100

tahmin = np.array([a1,a2,a3,a4,a5,a6,a7,a8,a9,a10,a11]).reshape(1,11)
print(model.predict_classes(tahmin))

if model.predict_classes(tahmin) == 0:
   print("Material is ABS")
else:
   print("Material is PLA.")
```