RESEARCH ARTICLE OPEN ACCESS

PREDICTION OF TENSILE STRENGTH OF ABS MATERIAL MANUFACTURED BY FUSED DEPOSITION MODELING USING MACHINE LEARNING

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ABSTRACT

Additive Manufacturing (AM) processes, such as Fused Deposition Modelling (FDM), are increasingly used to fabricate functional parts using Acrylonitrile Butadiene Styrene (ABS) material in which the tensile strength of 3D printed materials, such as those fabricated using Acrylonitrile Butadiene Styrene (ABS), is a critical mechanical property that determines their suitability for various applications. However, predicting the tensile strength of these parts remains challenging due to the complex interplay of various printing parameters. This study proposes a machine learning approach to predict the tensile strength of ABS parts based on their defined printing parameters such as Layer height, Infill density, printing speed, nozzle temperature and Bed temperature.

In order to conduct the experiment, Taguchi's Design of the Experiment is employed to create an L25 orthogonal array sample dataset. This dataset encompasses a range of combinations of the printing parameters, allowing for a comprehensive analysis of their effect on Tensile strength. The machine learning algorithms are then applied to this dataset, and their performance is compared to identify the most accurate model-fit.

Using a Universal testing machine the tensile strength value of each specimen is known. From these experiment values, A machine learning model was trained and validated, Various machine learning algorithms, like linear regression, random forest regressor, are employed to model and analyze the complex relationships between the printing parameters and Tensile strength. The best machine learning model is selected based on the least error.

INTRODUCTION

1.1 ADDITIVEMANUFACTURING

Additive manufacturing, often referred to as 3D printing, is a revolutionary manufacturing process that builds objects layer by layer from digital designs. Unlike traditional subtractive manufacturing methods, which involve cutting away material from a solid block, additive manufacturing adds material to create the desiredshape. This technology has gained immense popularity due to its versatility, cost effectiveness, and ability toproduce complex geometries with ease.

At the core of additive manufacturing is the digital design process. It starts with creating a 3D model usingcomputer-aided design (CAD) software. This model serves as a blueprint for the object to be printed. Thedesign can be customized and optimized to meet specific requirements, allowing for rapid iteration andprototyping.Once the digital model is ready, it is sliced into thin layers using slicing software. Each layer isthen sent to the 3D printer, which interprets the instructions and builds the object layer by layer. Additivemanufacturingtechniquesvarywidely,includingFusedDepositionModelling(FDM),Stereolithography(SLA),SelectiveLaserSintering(SLS), and others, each with its unique benefitsandapplications.

One of the key advantages of additive manufacturing is its ability to produce highly complex geometries thatare difficult or impossible to achieve with traditional manufacturing methods. This complexity allows for thecreation of lightweight structures, intricate designs, and integrated functionalities. For example, aerospacecompaniesuseadditivemanufacturingtoproducelightweightyetdurablecomponentsforaircraftandspacecraft,improving fuelefficiency andperformance.

Furthermore, additive manufacturing offers significant cost savings compared to traditional manufacturingprocesses, especially for low-volume production runs. By eliminating the need for expensive tooling andreducing material waste, companies can produce custom parts economically and on-demand. This flexibilityenablesagilemanufacturingstrategies,whereproductscanbequicklyadaptedtochangingmarketdemands. Additionally,additivemanufacturingfacilitatesdecentralizedproductionbyenablinglocalmanufacturing facilities or even individual users to produce parts on-site. This decentralized approach reducesleadtimes,transportationcosts,andrelianceonglobalsupplychains,makingmanufacturingmoreresilientand sustainable.

The applications of additive manufacturing span across various industries, including automotive, healthcare,consumer goods, and architecture. In the automotive industry, manufacturers use 3D printing to produceprototypes, custom tooling, andend-useparts, leading to fasterinnovation cyclesand improvedvehicleperformance.Inhealthcare,additivemanufacturingenablestheproductionofpatient-specificimplants,prosthetics,andmedical devices,offeringpersonalizedsolutionsand enhancingpatient outcomes.

Despite its numerous benefits, additive manufacturing also faces challenges, such as limited material options,surfacefinishissues,andqualitycontrolconsiderations.However,ongoingresearchandtechnologicaladvancementsareaddressingthesechallenges,expandingthecapabilitiesandapplicationsofadditivemanufacturing.

In conclusion, additive manufacturing is revolutionizing theway products aredesigned, prototyped, andmanufactured. Its ability to create complex geometries, reduce costs, and enable decentralized productionmakesitagame-changerinthemanufacturingindustry.Astechnologycontinuestoevolve,additivemanufacturingispoisedtounlocknewopportunitiesand reshapethe future ofmanufacturing.

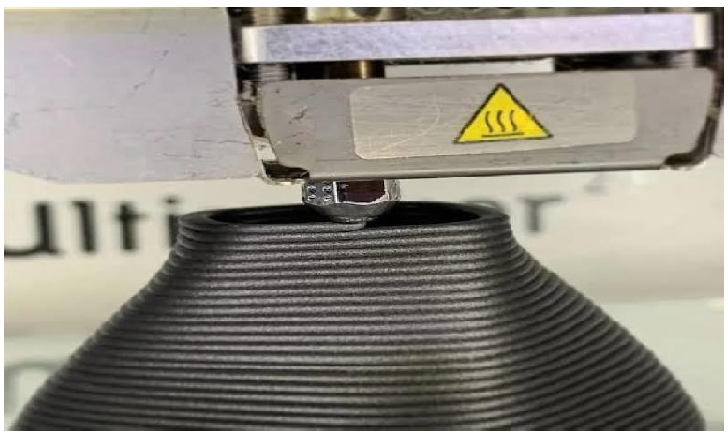


Fig1.1:3Dprinting

1.1.1 FUSEDDIPOSITIONMODELING

FusedDeposition Modelling(FDM)isapopular3Dprinting technologyusedforcreatingthree-dimensionalobjectslayerbylayer.Itworksbyextrudingthermoplasticmaterialthroughaheatednozzle onto a build platform. The material is deposited layer by layer, gradually building up the desiredobject.

One of the key components of FDM is the filament, typically made of materials like ABS (AcrylonitrileButadiene Styrene) or PLA (Polylactic Acid). These filaments are fed into the printer where they aremelted and extruded onto the build platform. The printer head moves in three dimensions, guided by acomputercontrolledsystem,toaccuratelydeposit thematerial accordingtothedesignspecifications.

FDM offers several advantages, including affordability, ease of use, and versatility. It is widely used invarious industries, including manufacturing, prototyping, and even in hobbyist settings. Its simplicitymakes it accessible to beginners, while its capability to produce functional prototypes and end-use partsappealsto professionals.

Overall, FDM is a widely adopted 3D printing technology known for its affordability, ease of use, andversatility.Whileitmaynotofferthehighestlevelofdetailorsurfacefinishcomparedtoothermethods, its accessibility and capability to produce functional parts make it a valuable tool in variousindustriesandapplications.

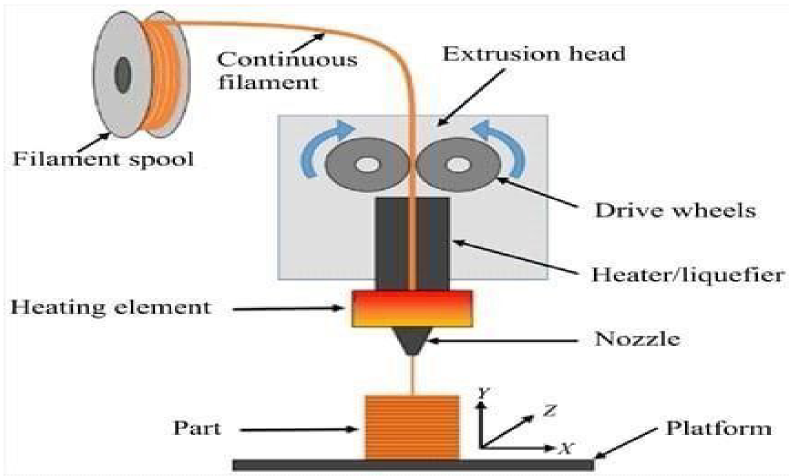


Fig.1.2 **:**FusedDepositionModellingprocess

1.1.2 LAMINATEDOBJECTMANUFACTURING(LOM)

Theprocess involvesplacing a layerof material, coated with adherentononeside, on to abuildplatform with the sticking side facing down. A heated roller is then passed over the material, ensuring itis adhesive to the platform securely. Next, the laser beam follows the profile of a specific slice of thedesired part, cutting through the layer of material. The lasered beam also cross hatches the areas that donot formpartofthe currentcrosssection, cuttingthrough thematerialagain.

In the LOM process, layers of material, typically paper, plastic, or metal foil, are bonded together usingheat and pressure. A computer-controlled laser or knife then cuts the shape of each layer based on thedigital. LOM offers several advantages, including relatively low cost compared to some other additivemanufacturing methods, the ability to create large parts, and the use of a variety of materials. However,it may have limitations in terms of the resolution and surface finish compared to other 3D printingmethodslike Stereolithography(SLA)or SelectiveLaserSintering (SLS).

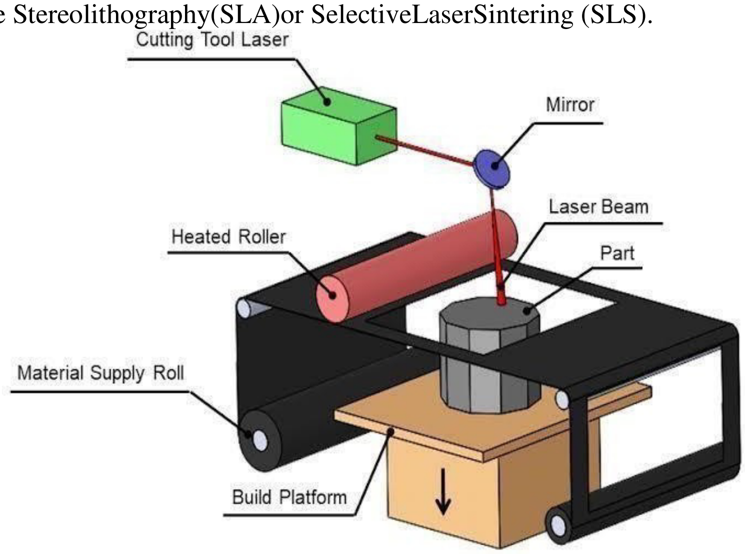


Fig.1.3:LaminatedObjectManufacturing(Lom)

LOM in 3D printing offers cost-effective production of large, strong parts with good surface finish, andwithout the needforsupportstructures.

LITERATUREREVIEW

1. **Areng al.** [1] This study employs Taguchi L18 statistical analysis to optimize key parameters in the FDMprinting of ABS focusing on layer height, infill pattern, infill density, print temperature, and annealingtemperature. Signal-to-noise ratio analysis identifies the optimal conditions for maximum tensile strengthas 0.16 mm layer height, 90% infill density, Gyroid infill pattern, 195°C print temperature, and 90°Cannealing temperature, achieving a predicted UTS of 35.79 MPa. Experimentally,a maximum tensilestrength of 37.15 MPa is measured, with Gyroid infill and annealing enhancing inter-layer adhesion andcrystallinity. The study underscores the effectiveness of the Taguchi methodology in optimizing ABSprintingparameters for superiormechanical properties.

2. **wendren & KA.** [2] In recent studies utilizing the Taguchi L9 approach, optimal dimensional accuracy inadditive manufacturing is achieved through varying parameter levels, with a focus on high extractiontemperatures for enhanced Tensile strength.Significance of Extraction temperature emerges as a dominantfactor,over shadowing the influence of wall thickness. Notably, this literature review acknowledges alimitation, emphasizing the examination's focus on only two factors within the additive manufacturingprocess.

3. **SurfGhanetal.**[3]Theapplicationofmachinelearningtechniques(MLTs)inpredictingthecompressive strength (C) of self-compacting concrete (SCC) represents a significant advancement in thefield of civil engineering. The study systematically evaluated six MLTs, integrating established artificialintelligence algorithms such as artificial neural network (ANN), adaptive neuro-fuzzy inference system(ANFIS), and extreme learning machine (ELM) with nature-inspired optimization algorithms like mothflameoptimizationalgorithm(MOFA)andwildhorseoptimizer(WHO).Throughameticulousexamination that addressed concerns related to input parameter consistency, dataset standardization, andcomprehensive model comparison, the research showcased remarkable accuracy in C prediction across allsix models. Notably, the ELM model fine-tuned with MOFA consistently outperformed its counterpartsacross variousmetrics

4. **Hatrix.DA.** [4]In describe the predicting process parameters, machine learning techniques can help tocircumventtheabove-mentionedconstraintsforFEM.Although largevolumesofdataare typicallyneeded for these strategies to be more accurate and generalizable. Combining FEM with machine learningcanprovideyoutheopportunitytosimulateaprocess(usingFEM),forecastoroptimiseprocessparameters toachievedesiredmechanicalqualities.Ontheonehand,finiteelementmodeling(FEM)isinmost cases used for numerical solutions of mathematical models and parameters' optimization, but thisprocessrequiresdeepknowledgeonphysicalpropertiesofmaterialandin-depthunderstandingofAM process.
5. **Anifat Olawoyin et al.** [5] The performance of the Multilayer Perceptron neural network and ARIMAmodels have been investigated in this research. Observations from the performance evaluation of themodels revealed that the four MLP architectures designed using tanh activation function outperform theARIMA model. Specifically, with the 4H411 model, they produce the best goodness of fit (R2 = 0.77) andlowest prediction error (RMSE = 0.099). The effect of adding more layers on the performance of amultilayer perceptron neural network is also investigated. Using the sigmoid activation function, a 2layerMLP having one neuron in the hidden layer has the best performance in term of prediction error (RMSE =0.103) and the coefficient of determination (R2 = 0.61) measures. The empirical evidence from

this studyindicates that adding more layers to a network configured using sigmoid function may not necessarilyimprovethepredictive power ofthenetworkandmayresult in performancedegeneration.

METHODOLOGY

Step-by-stepprocedurefollowedfortheflowoftheproject

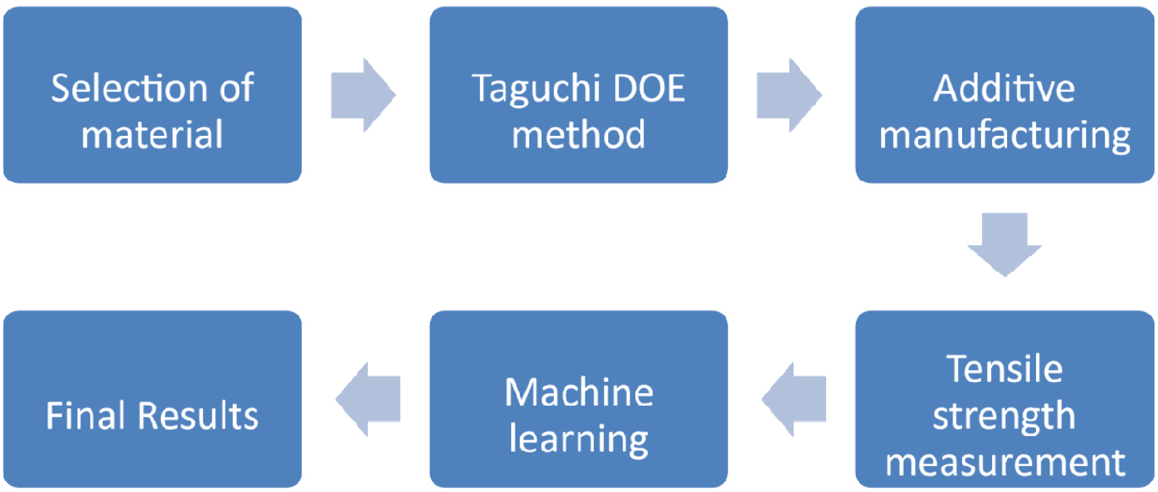


Fig3.1:Methodologyflowchart

Thereareseveralmaterialscommonlyusedin3Dprinting,eachwithitsuniquepropertiesandapplications.Hereare some ofthemostpopular ones:

3.1 MATERIAL

1. PLA (Polylactic Acid):PLAisabiodegradable thermoplasticthatiseasytoprintwithandisoften used forprototypes, educational models,and low-stress applications.

Fig3.2:PLA(PolylacticAcid)

2. ABS(AcrylonitrileButadieneStyrene):ABSisastrong,durableplasticthatcanwithstandhighertemperaturesth an PLA.Itiscommonlyusedinmanufacturing andfor functionalparts.

3. PETG (Polyethylene Terephthalate Glycol):PETG isadurable andeasy-to-printmaterialthatisstrongerand moreflexiblethan PLA. It isoften used formechanical parts

andprototypes.

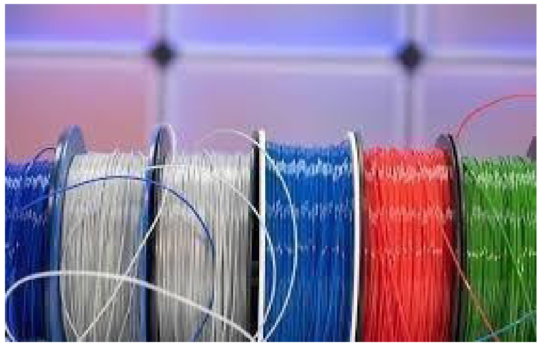


Fig3.3:PolyethyleneTerephthalateGlycol

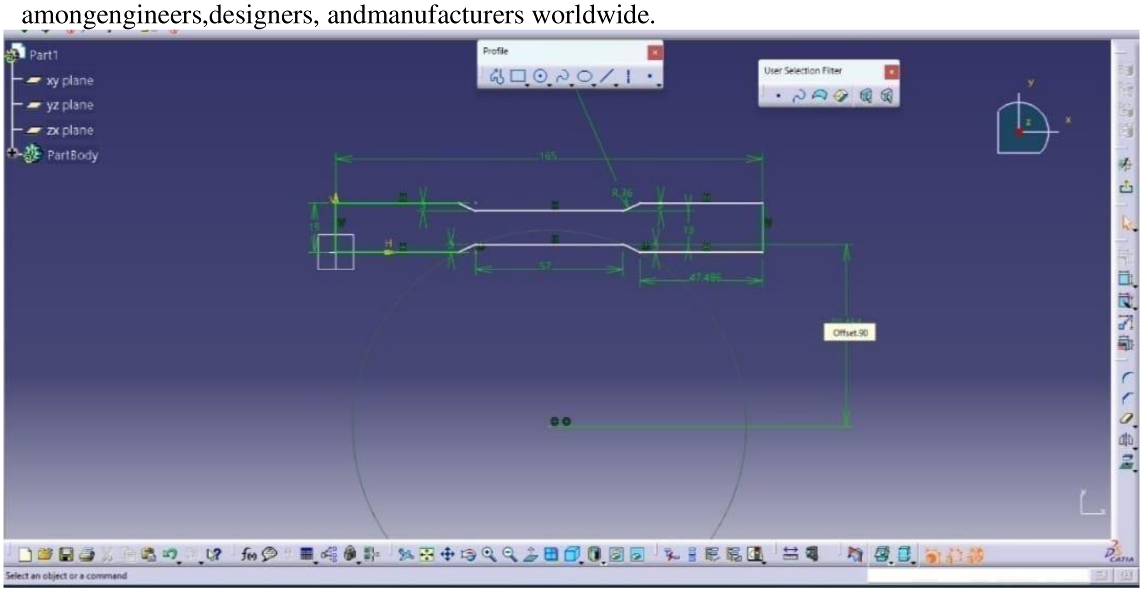
4. TPU(ThermoplasticPolyurethane):TPUisaflexiblefilamentthatisusedforprintingrubberlikeparts,such as phone casesandseals.
5. MetalFilaments:Metalfilamentscontainapercentageofmetalpowderandareusedforprintingmetal-likeparts,such asjewelryor prototypes.

3.1.1 ABS(AcrylonitrileButadieneStyrene):

ABS(AcrylonitrileButadieneStyrene)isapopularthermoplasticpolymerknownforitstoughness,impactresistance,andheatresistance. Here aresomekey propertiesand usesof ABS

3.2 DESIGNOFTHECOMPONENTINCATIA:

CATIA V5 is a powerful 3D modeling and design software used in various industries such as aerospace,automotive, and manufacturing. It offers a comprehensive suite of tools for creating, editing, and analyzing3D models, as well as for generating 2D drawings and assemblies. CATIA V5 is known for its advancedsurface modeling capabilities, whichallow usersto createcomplexshapesand designswith precision.CATIA V5's user-friendly interface and extensive range of functionalities make it a popular choice amongengineers,designers, andmanufacturers worldwide.



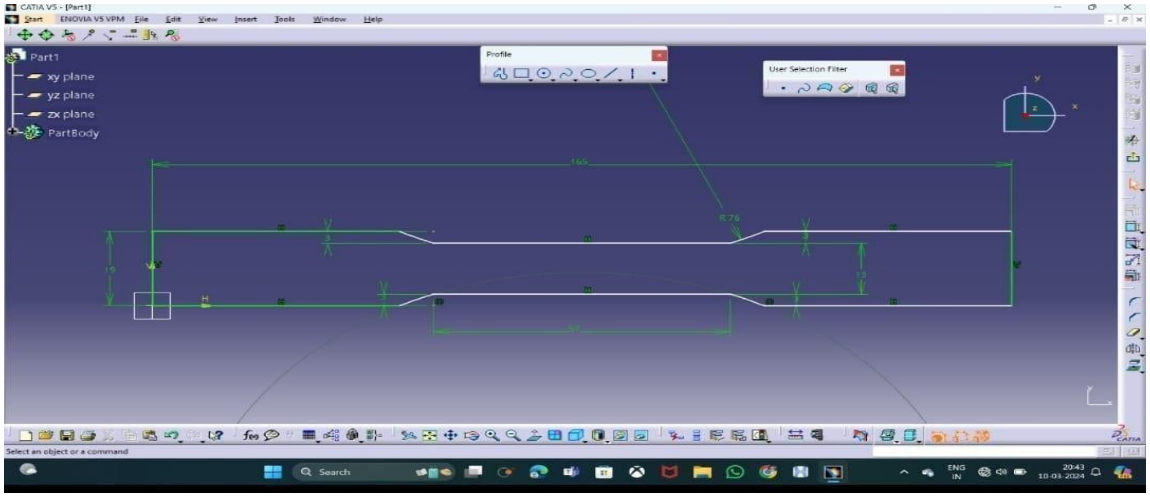


Fig3.5:Standardspecimenfortensiletesting

3.3 TAGUCHIDESIGNOFEXPERIMENT

Genichi Taguchi developed the Taguchi method, which aims to reduce process variation through a robustdesignofexperimentsandproduce veryhigh-quality productsat alowcostfor manufacturers.
The method involves using a Taguchi orthogonal array to organize the parameters that affect the process andthe dimensions at which they are varied. The Taguchi method differs from the factorial design in that it onlytestspairsofcombinations,ratherthanallpossiblecombinations.Thisapproachisusefulforidentifying whichfactorshaveanimpactonproductqualitywhileminimizingtheamountofexperimentationrequired,therebysaving time and resources.

SAMPLES PREPARATION THROUGH ADDITIVEMANUFACTURINGPROCESS

3.4.1 CREALITYSLICER:

CrealitySlicer is a slicing software designed forCreality3D printers.It allows users to prepare3D modelsfor printing by slicing them into layers and generating the necessary instructions for the printer. One keyfeatureofCrealitySlicerisitsuser-friendlyinterface,whichmakesiteasyforbothbeginnersandexperienced users to navigate. The software offers a range of customization options, allowing users to adjustsettings such as layer height, infill density, and print speed to achieve the desired print quality. Additionally,Creality Slicer supports a variety of file formats, making it compatible with most 3D modeling software.Overall, Creality Slicer is a versatile and powerful tool that simplifies the 3D printing process and helps usersproducehigh-quality prints

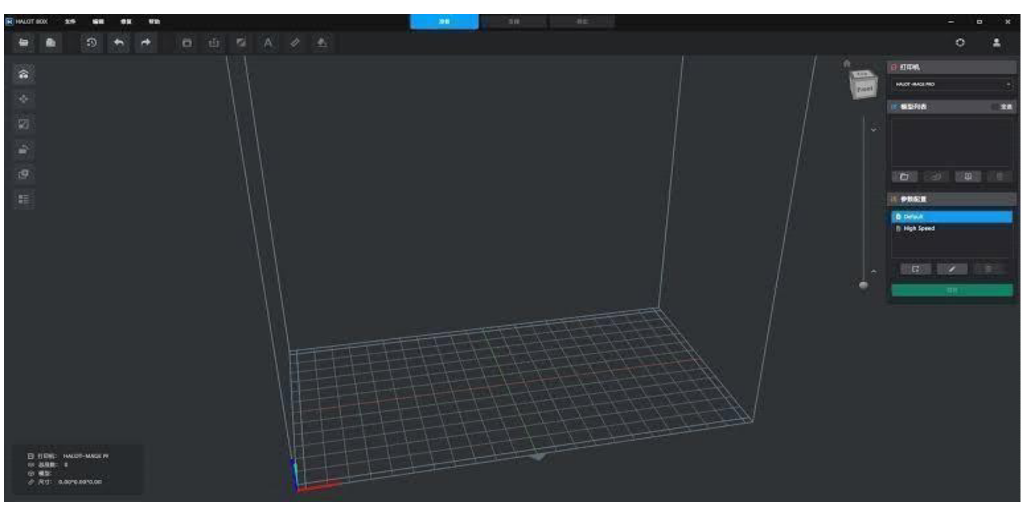


Fig3.11:Crealitysoftwareinterface

3.4.2 PRINTINGACOMPONENTINCREALITYMACHINE

Toprint acomponent usingaCrealitymachine,you'llneedtofollowthesegeneral steps:

Prepare Your Model: Use a 3D modeling software to create or download a 3D model of the component youwant toprint. Ensurethemodelisinaformat compatible withyourCrealitymachine(usuallySTL).

Slice the Model: Use a slicing software (e.g., Cura, Prusa Slicer) to convert the 3D model into a set ofinstructions (G-code) that the printer can understand. Adjust settings such as layer height, infill, and printspeedbased on your preferencesandthedesired quality of the print.

3.4 TENSILESTRENGTHMEASUREMENTUSINGUNIVERSALT ESTINGMACHINE (UTM)

UTMs determine tensile strength by subjecting a material sample to controlled tension until it fractures. Themachine measures the applied force and the corresponding elongation or deformation of the sample. Tensilestrength is then calculated by dividing the maximum force applied by the original cross-sectional area of thesample.Thismethodhelpsassessthematerial'sabilitytowithstandstretchingforceswithout breaking.

Tensile strength measurement using a Universal Testing Machine (UTM) involves subjecting a materialspecimen to a controlled tensile (pulling) force until it breaks. The specimen is typically dog-bone shaped toensure uniform stress distribution. The UTM grips the ends of the specimen and gradually applies a uniaxialtensile force, increasing at a constant rate. As the force increases, the machine records the correspondingelongation of the specimen. The tensile strength is calculated by dividing the maximum load (force) thespecimen withstands before breaking by its original cross-sectional area. This measurement is crucial fordeterminingthe material's abilitytowithstandtensileloadswithoutfailure, providingessentialdataforengineering applications and material selection. UTMs are versatile and can test various materials, includingmetals,polymers,andcomposites,makingthemindispensableinqualitycontrolandresearchanddevelopment.

VM

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MATERIAL SOLUTIONS
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TEST REPORT

Issued to:
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Mr. T. Shiva Shankar,
Mr. K. Laxmi Narasimha.
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Mallapur, Hyderabad – 500 076.

Test Report No : VMS/SR/0024
Test Report Date : 18.04.2024

SAMPLE PARTICULARS

Page 1 of 1

Sample Details	: ABS Tensile Samples
Sample Description	: ABS Tensile Samples
Quantity	: 25 No's
Packing Details	: Good
Test Required	: Tensile Strength, Elongation

Reference Number	: NA
Reference Date	: NA
Date of Receipt	: 15.04.2024
Date of Testing	: 15.04.2024
Date of Completion	: 16.04.2024

TEST RESULTS

S. No	Sample Details	Test Method	Results	
			Tensile Strength (MPa)	Elongation (%)
1	ABS- Layer Height – 0.15		16.44	4.43
2			26.50	6.23
3			9.73	8.53
4			22.96	5.46
5			14.79	6.24
6	ABS- Layer Height – 0.2		4.87	7.23
7			14.28	6.41
8			23.76	5.20
9			11.19	6.80
10			27.71	7.86
11	ABS- Layer Height – 0.25		21.15	6.11
12			7.45	3.37
13			6.62	5.14
14			29.64	4.41
15			10.16	5.94
16	ABS- Layer Height – 0.3		9.96	3.73
17			24.46	5.70
18			4.42	5.40
19			31.16	7.00
20			29.16	5.27
21	ABS- Layer Height – 0.35		33.17	3.87
22			24.39	8.17
23			34.16	4.09
24			34.60	3.91
25			13.11	3.56

Disclaimer-1: This report relates only to the particular sample submitted for test.
Disclaimer-2: Sampling is done by customer

END OF THE REPORT

REVIEWED AND AUTHORIZED BY

VIRTUE META-SOL * Hyderabad *

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VMS/QF/7.8/TRF Rev 04 Mar '24

Fig3.15:Tensilestrengthtestreport

MACHINELEARNING

Machine learning is a branch of artificial intelligence that focuses on developing algorithms and statisticalmodels that allow computer systems to learn from and make predictions or decisions based on data. Itinvolves the use of algorithms that iteratively learn from data, enabling computers to find hidden insightswithout being explicitly programmed where to look. Machine learning is used in various applications, fromspam detection to image recognition, and is a fundamental technology driving advancements in artificialintelligence.

4.1 MachineLearningTechniques

ML techniques are generally categorized into 4 groups: supervised learning, unsupervised learning, semisupervisedlearning, andreinforcedlearning (Figure 1). In thissection, the theoriesand ideasofeachcategoryofML techniqueswillbe discussed indetail.

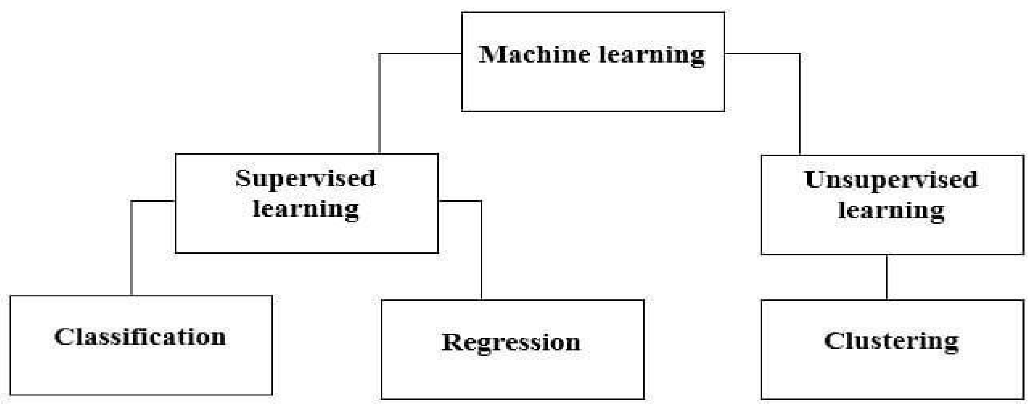

Fig4.1:MachineLearningTechniques

4.1.1 SupervisedLearning

Supervised learning involves training an algorithm on a group of data, in which each training point contains alabel.Thislabelsignifiesaparticularclassthatthetrainingpointbelongsto.Supervisedalgorithmsthentryto identify the decision boundaries that split the clusters of data. Supervised learning algorithms model therelationship between the input features and the labeled outputs. Thus, it is able to predict input features for“desired”outputs.

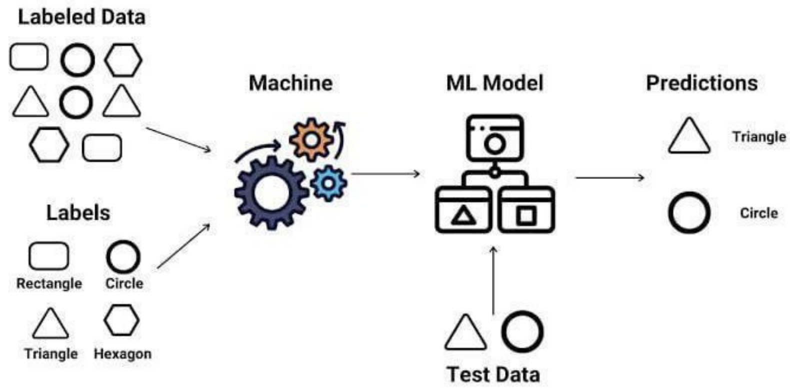

Fig4.2:SupervisedLearning

Some examples of supervised learning algorithms used in AM field are Naive Bayes (Wu, Phoha et al.2016,Bacha, Sabry et al. 2019), Decision Trees (Wu, Phoha et al. 2016), Linear Regression, convolutional neuralnetwork (CNN) (Gu, Chen et al. 2018, Ludwig, Meyer et al. 2018, Pham, Lee et al. 2018, Scime and Beuth2018, Shevchik, Kenel et al. 2018, Yuan, Guss et al. 2018, Zhang, Hong et al. 2018, Francis and Bian 2019,Khadilkar, Wang et al. 2019), genetic programming (Vosniakos, Maroulis et al. 2007, Rong-Ji, Xin-hua et al.2008, Jiang, Liu et al. 2014, Vijayaraghavan, Garg et al. 2014, Garg, Lam et al. 2016, Yamanaka, Todoroki etal. 2016), long short term memory (Koeppe, Hernandez Padilla et al. 2018), artificial neural network (ANN),particle swarm algorithm (Asadi- Eydivand, Solati-Hashjin et al. 2016), k-nearest neighbour (KNN) (Wu,Song et al. 2017), radial basis function (Vahabli and Rahmati 2016), Siamese neural network (He, Yang et al.2019),and supportvectormachine(SVM)(Gobert, Reutzeletal. 2018).

4.1.2 UnsupervisedLearning

Unlike supervised learning, unsupervised learning algorithms require no human expert to label the dataUnsupervised methods extract features in the input data that are unlabelled and classify the data throughselftaught rules. Thus, these models are usually applied to identify hidden or unknown relationships amongthe data

Fig4.3: UnsupervisedLearning

PARTQUALITY/PROCESSOPTIMIZATION

Processoptimizationisoftenperformedwhennewmaterialsornewprocessesaredeveloped. Processoptimization of AM processes can be performed to obtain certain characteristics of the 3D printed parts withvariationintheprocessparameters.ProcessparametersaffectthepartpropertiesforAM(Yu,Singetal.2019, Kuo, Chua et al. 2020). A database of process-structure-properties (PSP) relationship for acertain AMprocess and materials would enable the proper selection of the parameters based on the available informationin the database . The PSP relationship is often complicated due to the high dimensionality of the processparameters, making it difficult to establish the governing mathematical formula of the process. Due to itscomplex nature, ML algorithms have been used to determine the PSP relationships for many AM.Gan et al.attemptedusingSOM,anunsupervisedMLtechnique,toidentifytheprocess-structure-propertiesrelationship of the directed energy deposition process for Inconel 718(Gan, Li et al. 2019). Multipleobjective optimizations of the process parameters can be achieved from the large and high dimensionaldataset,whichisobtainedfromsimulationandvalidatedwithexperimentalresults,withthehelpofvisualizedSOM.

4.2 STEPSINVOLVEDINMACHINELEARNING

Fig4.5: StepsInvolved InMachineLearning

CONCLUSION

The objective of our project was to develop a predictive model for Tensile strength of Acrylonitrile ButadieneStyrene (ABS) material within the context of Additive Manufacturing (AM), by using different MachineLearning (ML) techniques. We aimed to achieve this by scrutinizing critical printing parameters, namely layerheight,infilldensity, printingspeed, Bedtemperatureandnozzle temperature.
Toachievethiswehaveuseddifferentmachinelearningtechniquespreciselylinearregression,Ridgeregression, Gradient boosting algorithm, Random forest, KNN, Decision tree regression and It was concludedthatGradientboostingalgorithmis thebest machinelearningalgorithmwhichispredictingtheTensilestrengthwithminimumerror.
Tensile strength prediction can help in optimizing manufacturing processes. By analyzing the relationshipbetweenprocessparametersandTensilestrength,machinelearningmodelscanidentifytheoptimalsettingsfor achieving suitability for various applications. This can lead to improved efficiency, reduced costs, andenhancedproductivity.
It was concluded that exploratory data analysis helped a lot to understand the data which is very much helpfulin the selection of suitable machine learning model and to know the relationship between the parameters.Different statisticaltechniques helptofindthefeatureorvariable importanceinthisproject.

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