Classification of Aluminum, Magnesium and Tri-Boride Metal composites using Deep Learning Approach

[1]Harini M Dev, [2]Vinod Kumar M S

[1]M.Tech Student, [2]Assistant Professor
[1] Department of Mechanical Engineering,
[1]VTU Center for PG Studies, Mysuru, India

Abstract: The study of metal composites and its properties is an essential part of the field of study in the area of Composite materials. The composites of metals contributes towards the strength of metal structures being used in various Industrial applications such as Aviation, Construction and Production units etc. Various types of metal compositions will be considered in the different areas of applications. Among them, the Aluminum composites are very special and mostly used in lot of metallic design solutions. The composites of Aluminum, Magnesium and Tri-Boride is one such composition which has been the study of material in this work. Amongst various traditional studies, the classification of percentage of compositions is one of the important field of study. In this work, a novel AI driven computational approach comprising of Deep learning technique has been presented to automatically detect and classify the concentration of metal composites of the above three material on the microscopic images obtained from Scanning Electron Microscope(SEM). This approach outperforms other traditional approaches in a way that does not require any standard mechanical process and seamlessly will be able to figure out the concentrations for any unknown samples.

Index Terms **– Composite Materials, Deep Learning, Aluminum, Magnesium, Tri-Boride, ResNet34**

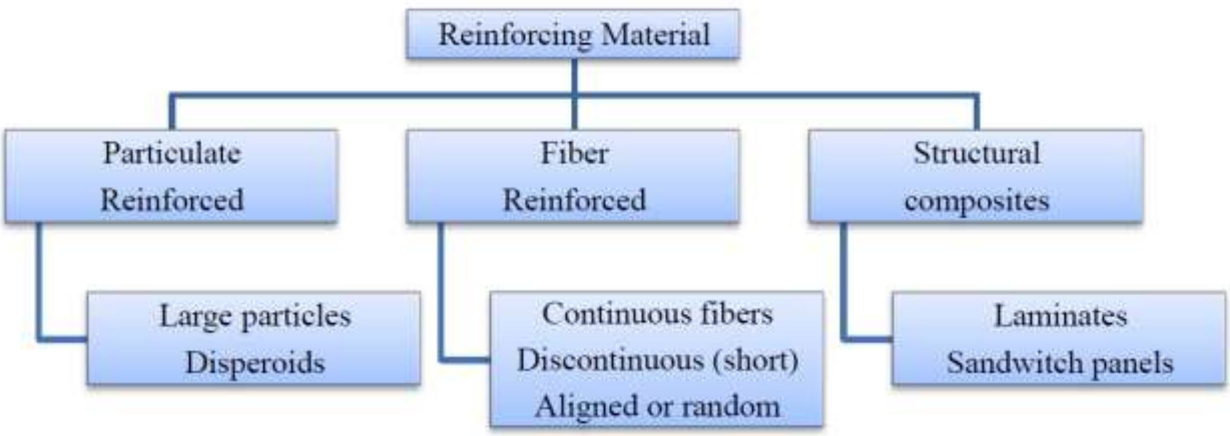
I. INTRODUCTION

1.1 A brief on Composites

A composite material is defined as a structural material created synthetically or artificially by combining two or more materials having dissimilar characteristics. The constituents are combined at macroscopic level are not soluble in each other. One constituent is called as matrix phase and the other is called reinforcing phase. Reinforcing phase is embedded in the matrix to give the desired characteristics. Reinforcing phase: Fibres, Flakes, Particulates, and Whiskers etc. Matrix phase: Continuous phase (Epoxy resin, Unsaturated Polyester etc)

1.1.1 Classification of composites

Classification of composites is done based on both geometry for reinforcing material and the type of matrix materials shown in Figure. 1. Classification scheme for the composite is as illustrated below:



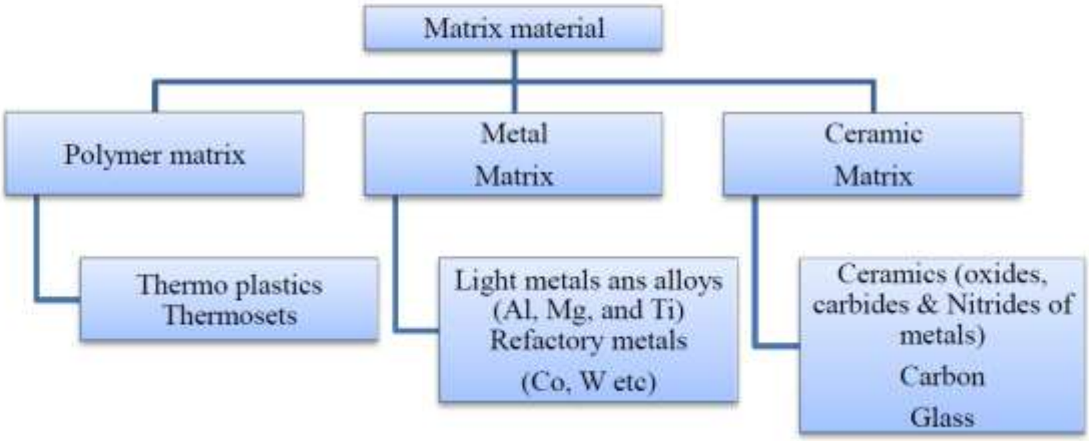


Figure. 1 Brief Classifications of Composite Materials

1.2 Analysis of Composites

Analysis of Composites often the use of multiple analytical techniques to properly characterize the materials and the interfaces between them which often contribute in important ways to the properties of the materials such as Low density, High Specific Strength, High Specific Modulus, High Thermal Conductivity, Good Fatigue Modulus, Control of Thermal Expansion, High Abrasion and Wear Resistance.

1.2.1 Challenges in Composite analysis

Following a detailed understanding of the properties of the composite materials, it is essential to understand the reliability and failure resistant properties of the composite materials whether it belongs to matrix compositions or reinforced fiber composites. The application of the composite material are found in the design of aerospace technology, construction, marine, electronic components and many other industries because of their high specific strength and stiffness combined with low density when compared with conventional materials allowing for weight reduction in the finished product. Hence, it is very significant to address the failure properties of the composite materials

1.3 Objectives of Composites analysis

The analysis of the strength and the failure properties of the composites requires study of the microstructures through an intense observation of the microelements of exploring the various properties of the same. This is possible by observing the microstructure at microscopic levels using imaging devices. But as the observation is time consuming and laborious, there is a need for an automated process such computational approach involving image processing abilities. Further, the advent of machine learning and deep learning approaches have given additional impetus in the exploration of the microstructures of the composites. Keeping these abilities in mind it has been proposed in this work to develop an automated computational or machine or deep learning based approaches address the objectives of segmentation or classification or detection of the microstructural elements.

1.3.1 Traditional approaches

Traditional approaches include manual analysis of microstructure elements in the composites through scanning electronic microscope and through observations of various phases at different zoom levels .this also involves quantification and observing various morphological patterns of different materials under poor vision environment and varied contrast. This process is quiet cumbersome and time consuming further leading to erroneous calibration of the significant parameters under study.

1.3.2 Challenges in traditional approaches

Composites are plagued by problems such as low through-thickness mechanical properties, poor impact damage tolerance, and anisotropic properties. Traditional approach to composite repair development is to choose an overall repair concept configuration for a particular type of structure specifying the damage type, damage size of parent material. With these challenges, quoting the inability of traditional method in accurately extracting the required properties, it is evident that there is a need for automated approach to study the properties of microstructure elements

1.4 Problem Definition

In this work a novel computational idea has been proposed to detect and classify the Aluminum, Magnesium and Tri-Boride concentrations into five different classes based on the concentration of the above materials. The five classes are as follows 1. Aluminum 2. Al+Mg with 3% Triboride 3. Al+Mg with 6% Triboride 4. Al+Mg with 9% Triboride and finally 5. Al+Mg with 12% Triboride using deep learning approaches.

II. LITERATURE REVIEW

2.1 Challenges in Composites

Various works in the recent past have proved the significance of the study of the microstructure analysis, which are discussed as follows. Gowda et al. [1] studied that the properties of jute fibre reinforced with polyester composites and they concluded that the jute- polyester composites shows better strength than the wood based composites. Das et al. [2] have studied on bio composite films and the effect of stress transfer. They concluded that tensile strength of bio composite films increased by in the range of 51% to 197% which is compared to the unreinforced one. Mantry et al. [3] have investigated the role of Silicon Carbide (SiC) particles loading on the mechanical and tribological properties of jute-epoxy based hybrid composites. Based on this study, they reported that the mechanical properties of unfilled SiC particles increases with fiber loading and in another case the tensile strength is decreases with filled SiC particle composites. Satapathy et al. [4] studied on effect of fiber loading on jute epoxy composites. They concluded that, flexural strength is increases with increases in fiber load and decreases trend in case of increases in the wt% of filler content. Osmani et al. [5] investigated on mechanical properties of SiO2 filled G-E hybrid composites and reported that shear, impact and tensile strength were decreases with increasing in the wt% of SiO2 content. But flexural strength of the same composites increases with increases in particulate content. Satapathy et al. [6] studied on effect of SiC particles loading on jute epoxy composites. They concluded that, the interlaminar shear strength is increases with increases in SiC particles. Jute is multicelled in structure. Jute fiber is generally derived from the steam of a jute plant. It is an annual plant that grows to 2.5-4.5 m and flourishes in monsoon climates [7]. Jute is a lingo-cellulosic fiber because its major chemical constituents are lignin and cellulose.

The thermal and electrical conductivity, biological degradation, proneness to mildew and moths, ability to protect from heat, cold and radiation, reaction to sun and light, etc. are determined by cellular constitution and morphology [8]. High quality and new uses of this fiber can create more job opportunity in the rural sector [9]. Jute has also got applications in the automobile industry and packing materials. Unlike cotton and most of the food crops, jute does not require any pesticides and fertilizer and hence is a pure green‖ agro-product. Islam and Alauddin [10] reported a comparative study among the major jute producing nations. It has been found that India is one of the leading jute producing nations more than the past two decades. On jute-epoxy based composites, Mishra et al. (2000), Gassan and Bledzki (1997) and Maschinenwesen et al. (2006) studied and concluded the following results: Mishra et al. [11] investigated the role of effect of the 50 wt% of fiber loading on jute-epoxy reinforced composites. They found the mechanical performance of the effect of 50 wt% of fiber loading on composites. They concluded that mechanical properties like impact and flexural strength showed enhanced results in the bleached composites, as compared to the controlled case. Mishra et al. [12] also investigated that the impact energy of jute/flax/hemp epoxy based composites. They concluded that the effect of chemical modification shows enhanced good bonding and in turn resulted in better impact strength. Gassan and Bledzki [13] evaluated the mechanical performance of fiber and matrix by the effect of coupling agent. They concluded that a tensile property of 50 wt% bleached case shows lesser than that of unbleached condition. And the other mechanical properties like impact of bleached case and flexural of raw jute epoxy, considering bleached as base condition, in both the properties bleached condition shows better results as compare to the control and raw case respectively.

Maschinenwesen et al. [14] studied the effect of fiber surface treatment on composite materials. They concluded that the effect of surface treatment decreases the water uptake and diffusivity of composites as compared to the untreated state Siddhartha et al. [15] have investigated titanium dioxide (TiO2) reinforced epoxy functionally graded composites. They concluded that incorporation of TiO2 particles into epoxy mixture shows better mechanical properties in comparison to the unfilled hybrid composites. Shi et al. [16] studied on two parameters of the filler materials. One is about crystal structure of the filler and another parameter is shape of the filler material on the coefficient of friction and wear properties. They reported that the coefficient of friction of PTFE based composites are weakly depends on filler shape and more strongly depends on crystal structure of the filler material. Yamamoto et al. [17] investigated that the effects of silica particles characteristics on evaluation of mechanical properties of SiC particle epoxy resins. They concluded that the structure and shape of SiC particles have significance effects on the mechanical properties. Patnaik et al. [18] made a comparative study on mechanical properties of G-P composites by influencing the different ceramic fillers. They reported that the properties of composite materials are highly influenced by the effect of size and shape of the filler materials.

Further, various deep learning approaches have been implemented to to study the microstructure analysis as shown in Sergi et.al[19] and Aly et.al [20]

III. DATA SET

3.1 Data Collection

As an initial stage of the work, the data preparation is the most challenging task, as the total number of images required for a machine learning or deep learning models should be enormous. The following approaches have been followed initially to explore possible sites of data collection. One more important requirement for a machine learning approach is to have the ground truth for every image set to be generated.

3.1.1 Interaction with Researchers

Few researchers in the field of the composite structure analysis were consulted to know the source of data and a total 40 SEM images were obtained, comprising 8 images from each class.

3.2 Image Data set

As the deep learning methods requires huge amount of dataset, the initial challenge was to generates patches of 150X150 resolution from each images and the dataset was subjected to augmentation techniques such as rotation by 30, 60 and 90 degrees, Flip right and left, Flip top and down. Finally, a total of 23,000 patches were generated form the original 40 images.

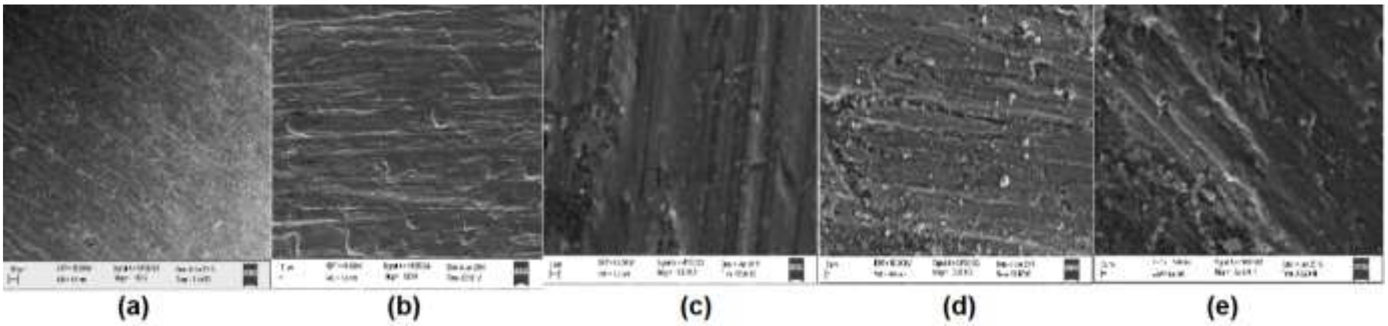


Figure. 2 Sample SEM images (a) Aluminum (b) Al+Mg with 3% Triboride (c) Al+Mg with 6% Triboride (d) Al+Mg with 9% Triboride (e) Al+Mg with 12% Triboride

IV. PROPOSED METHODOLOGY

In this a detailed discussion about the proposed methodology has been illustrated.

4.1 Stages of Proposed Plan of action

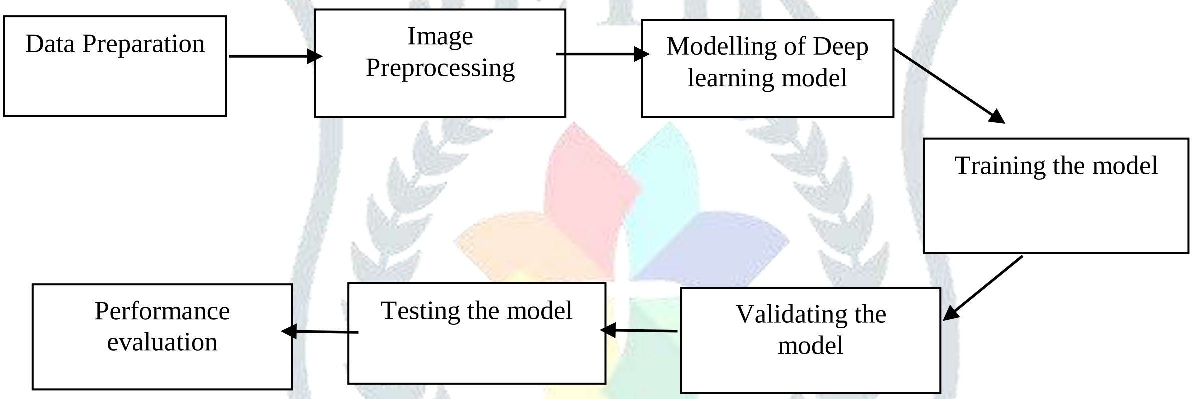


Figure. 3 The flow diagram of Proposed Methodology

4.2 Data Preparation

As discussed in second chapter the image data set will be explored from various sources of internet and other literature studied the image set collected will be associated with the labels or the ground truth annotated within the image or in separate label file indicating the features of interest to be extracted from a unknown sample. This data sets will be used for training as discussed in the subsequent sections

4..3 Modelling of Deep Learning approach

In this section the proposed transfer learning based Deep learning approach is presented. Here, a pre-trained model is used for training the exiting dataset to avoid over fitting during the training. The pre-trained model adapted here is the RESNET32 model.

4.4 Training, Validation and Testing

The deep learning algorithm involve the training of image data set with known labels to an expected accuracy of learning. The learning accuracy of the model will be validated using a validation step during a training process. Irrespective of whether the objective is segmentation, extraction or classification, the accuracy of the model will be tested using an unknown sample during the testing phase.

V. RESULTS AND DISCUSSION

The experimentation was conducted using a popular deep learning model called ResNet34. The model of the same is as shown in figure 4.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

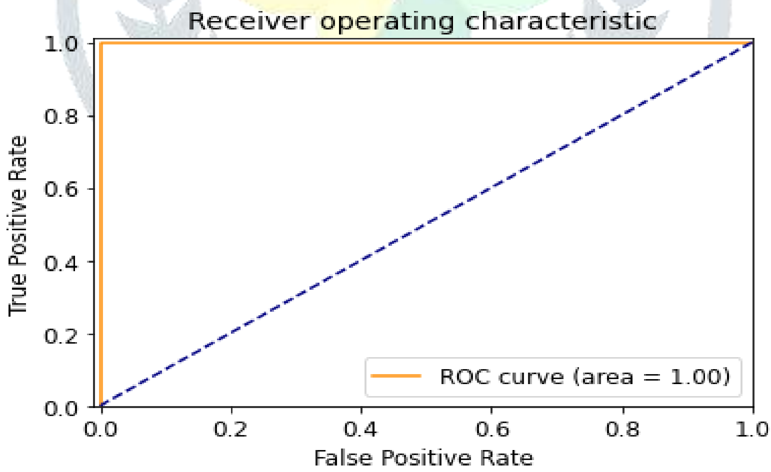
Figure 4. The ResNet34 deep learning model

A total of 23000 patches of the SEM slides have be fed into the model to generate the trained model and the same is going to be evaluated for validation accuracy, for which we got 99.74% accuracy. The epoch wise accuracy as shown in figure 5.

epoch	train_loss	valid_loss	accuracy	time
0	0.188803	0.071321	0.975000	26:25
1	0.135982	0.030330	0.992373	25:50
2	0.041209	0.013980	0.995763	25:59
3	0.012687	0.006840	0.997458	25:50

Figure 5. Results of every epoch of training and validation

The model hence trained is tested on a test set and the AUC (ROC curve) generated is equal to 1. The AUC of the same is depicted in Figure below.



VI. CONCLUSIONS

The proposed project idea is an endeavor to address the various challenges posed during the study of microstructure properties in a given composite material. The objective of the study is to classify the various metal composites in an Aluminum, Magnesium and Tri-Boride composition. A novel deep learning based techniques adapting ResNet34 model has been effectively used to classify the Aluminum composites into various classes with an accuracy of 99.74%. The model has shown an ROC of 1, while testing over a test set. This idea has been proposed as an automated solution, based on computational or AI based approach to outperform the traditional methodologies in addressing the challenges in the study of composite materials

REFERENCES

[1] Gowda T. M, Naidu A. C. B, and Chhaya R, (1999). Some Mechanical Properties of Untreated Jute Fabric-Reinforced Polyester Composites, Composites Part A: Applied Science and Manufacturing, 30(3), pp. 277- 284

[2] K. Das, D. Ray, N. R. Bandyopadhyay, S. Sahoo, A. K. Mohanty, M. Mishra, (2011). Physico-Mechanical Properties of the Jute Micro/Nanofibril Reinforced Starch/Polyvinyl Alcohol Biocomposite Films, Composites: Part B, 42, pp. 376–381.

[3] S. Mantry, A. Satapathy, A. K. Jha, S. K. Singh, A. Patnaik, (2011). Preparation, Characterization and Erosion Response of Jute-Epoxy Composites Reinforced with iC Derived from Rice Husk, International Journal of Plastics Technology, 15, pp. 69-76.

[4] A. Satapathy, A. K. Jha, S. Mantry, S. K. Singh, A. Patnaik, (2010). Processing and Characterization of Jute–Epoxy Composites Reinforced with SiC Derived from Rice Husk, Journal of Reinforced Plastics and Composites, 29, pp. 2869-2878

[5] Osmani, (2009). ―Mechanical Properties of Glass-Fiber Reinforced Epoxy composites Filled with SiO_2 Particles‖, Journal of Reinforced Plastics and Composites, 28, pp 2861-2867.

[6] A. Satapathy, A. K. Jha, S. Mantry, S. K. Singh, A. Patnaik, (2010). Processing and Characterization of Jute–Epoxy Composites Reinforced with SiC Derived from Rice Husk, Journal of Reinforced Plastics and Composites, 29, pp. 2869-2878

[7] J. Summerscales, N. P. J. Dissanayake, A. S. Virk, W. Hall, (2010). A Review of Bast Fibres and their Composites. Part 1 – Fibres as Reinforcements, Composites: Part A, 41, pp. 1329–1335.

[8] C. Roul, (2009). The International Jute Commodity System, Northern Book Centre, New Delhi."Role of TiO2 Filler Loading on Mechanical and Tribological Behaviour of Jute-Epoxy ybrid Composites"

[9] C. Alves, P.M.C. Ferrão, A. J. Silva, L. G. Reis, M. Freitas, L. Rodrigues, D. E. Alves, (2010). Eco design of Automotive Components Making use of Natural Jute Fiber Composites, Journal of Cleaner Production, 18, pp. 313– 327.

[10] M. S. Islam, M. Alauddin, (2012). World Production of Jute: A Comparative Analysis of Bangladesh, International Journal of Management and Business Studies, 2, pp. 14-22.

[11] Mishra, H.K., Dash, B.N., Tripathy, S.S., & Padhi, B.N. (2000). A Study on mechanical performance of jute –epoxy composites. Poly.-Plast.Technol. Eng., Vol. 9, No. 1, pp. (187–198)

[12] Mishra, H.K., Dash, B.N., Tripathy, S.S., & Padhi, B.N. (2000). A Study on mechanical performance of jute –epoxy composites. Poly.-Plast.Technol. Eng., Vol. 9, No. 1, pp. (187–198)

[13] Maschinenwesen, D.F. (2006). Investigation on jute fibres and their composites based on polypropylene and epoxy matrices. PhD Dissertation, University of Dresden Vietnam.

[14] Gassan, J.,& Bledzki, A.K. (1997). Effect of Moisture Content on the Properties of Silanized Jute-Epoxy Composites. Polym Compos., Vol.18, No. 2, pp. (179-184)

[15] Siddhartha, A. Patnaika, and A. D. Bhattb, (2011). ―Mechanical and dry sliding wear characterization of epoxy-TiO_2 particulate filled functionally graded composites materials using Taguchi design of experiment,‖ Materials & Design, vol. 32, no. 2, pp. 615–627.

[16] Y. J. Shi, X. Feng, H. Y.Wang, C. Liu, and X. H. Lu, (2007). ―Effects of filler crystal structure and shape on the tribological properties of PTFE composites,‖ Tribology International, vol. 40, no. 7, pp. 1195–1203

[17] Yamamoto I, Higashihara T and Kobayashi T, (2003). Effect of silica particle characteristics on impact/usual fatigue properties and evaluation of mechanical characteristics of silica-particle epoxy resins, JSME International Journal-Series A: Solid Mechanics and Material Engineering, 46 (2), pp. 145-153.

[18] Patnaik A, Satapathy A, Mahapatra S. S and Dash R. R, (2009). A Comparative Study on Different Ceramic Fillers affecting Mechanical Properties of Glass-Polyester Composites, Journal of Reinforced Plastics and Composites, 28 (11), 1305-1318.

[19] Evsevleev, S., Paciornik, S. and Bruno, G., 2020. Advanced Deep Learning‐Based 3D Microstructural Characterization of Multiphase Metal Matrix Composites. *Advanced Engineering Materials*, *22*(4), p.1901197.

[20] Badran, A., Marshall, D., Legault, Z., Makovetsky, R., Provencher, B., Piché, N. and Marsh, M., 2020. Automated segmentation of computed tomography images of fiber-reinforced composites by deep learning. *Journal of Materials Science*, *55*(34), pp.16273-16289.