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Multimedia Teaching Learning Methodology and Result Prediction System Using Machine Learning

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Abstract**—**With the availability of Multimedia Technology for the teaching-learning process, it becomes easier and convenient to enhance the learning of professional courses. Technical concepts conveyed with the help of Multimedia teaching methodology (such as Google classroom, Learning Management System (LMS), virtual lab, audio, video, animations, PowerPoint presentations, YouTube, and digital lab) for the course Energy Conversion-1 assists students to understand very complex and challenging concepts easily. The existing work does not incorporate Multimedia Technology for Energy Conversion-1 course to Third Year Mechanical Engineering students in semester VI. To identify which teaching methodology is better, this work proposes the analysis of the results for different academic years adopted different teaching methodologies, namely, traditional and Multimedia based. The approach uses a hand-crafted statistical t-value measure to prove that Multimedia based teaching method is much better than a conventional teaching method. Moreover, the existing work does not incorporate the comparison of ML models to predict the end semester examination (ESE) result of the students in the course Energy Conversion-1. This work also proposes the development of the ESE result prediction system using K-NN, SVM and Decision tree ML algorithms and the comparison of K-NN, SVM and Decision tree ML algorithms to predict the ESE result for the course Energy Conversion-1. SVM, K-NN and Decision Tree model predicted the ESE result with 78%, 70% and 70% accuracy, respectively. The comparison showed that SVM model predicted result with 78% accuracy, best fitting data**.**

Keywords**—**Energy Conversion-1; Machine Learning; Mechanical engineering; Multimedia Technology; Third year students

JEET Category**—Research**

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.INTRODUCTION

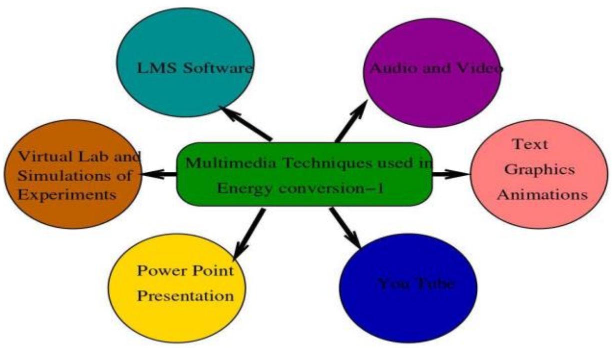


Fig 1: Multimedia Techniques for Energy Conversion−1.

Teaching methodology is an important part of teaching learning system as the proper teaching way of teachers largely affects the understanding of students and enhancing the interest in writing, research etc. [1]. The easier and wider availability of information about different teaching techniques strengthns the faculty. Information conveyed with the help of Multimedia teaching methodology helps to understand very complex and difficult concepts in an easy way. The existing work does not incorporate the the use of Multimedia Technology for Energy Conversion-1 course to Third Year Mechanical Engineering students in semester-VI. The traditional techniques for teaching learning process do not provide the power point presentations, use of LMS software, audio, video. In other words, the traditional teaching methodology includes chalk and black board [2]. In this conventional approach, the students are sitting in rows. In general, the teacher's place is in front of the students, thus making him visible to all the students. The teacher is explaining, instructing, and giving information to all the students. He uses chalk to write required points on the black board and duster to erase from the blackboard. Here, the information flow is from faculty to student, as it is faculty centered and the students are passive learners.

In this work, we are using Multimedia techniques; therefore, the multimedia classroom teaching methodology can be adopted to teach the course Energy Conversion-1 [3], [4]. In the multimedia classrooms, the seating arrangement of the students is flexible and can be modified whenever required. All the equipments required for the study are available, thus making the students to enjoy the learning [5]. Here, the students can sit in the comfortable chair and have opportunity to move around the furniture for group discussions. They can connect the computers to the equipments and do the experiments with the help of software, results in abundant knowledge gain of various areas [6], [7]. It also enhances the interest in creation of brainstorming ideas. Fig.1 illustrates, different multimedia techniques used for teaching the course Energy Conversion-1, there exist different forms of multimedia teaching methodology, namely, audio, video, Animations, virtual lab, Google classroom, Text, Learning Management System (LMS), Power Point presentations, digital lab etc., which improves the interaction between teacher and student, also provides an ample of knowledge about the course to the students.

Multimedia Technology strengthens the professional education activity by enhancing the interaction between faculties and the learners. There are no restrictions such as time and space for Multimedia Technology, thus, making it an anytime and anywhere tool of educational technology for professional courses. This has reformed teaching and learning methodologies.

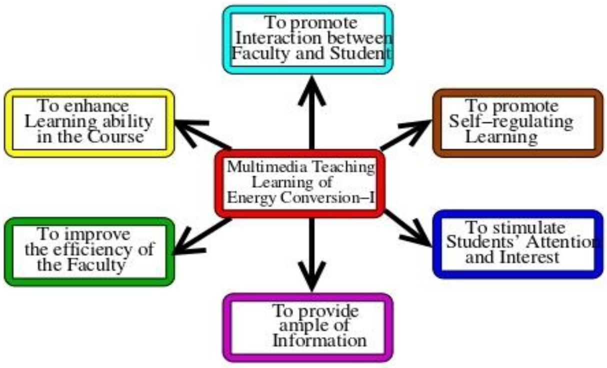


Fig 2: Multimedia Benefits in Teaching Learning of EC−1.

Fig. 2 illustrates, with the help of Multimedia technology teaching approach for Energy Conversion-1, there exist an abundant advantages, namely, stimulation of students attention and interest, promotion of self-regulating learning, promotion of interaction between faculty and student, enhancing learning capability of students in this course, improving the efficiency of teacher, and providing an ample of information to the students. Multimedia has the ability to convert academic endeavor from instruction and learning to research and dissemination of knowledge.

Machine learning algorithms are the best for the categorical predictions. Therefore, we incorporated SVM, K-NN and Decision Tree ML models for the ESE result prediction of Third year Mechanical engineering students. Support Vector Machine is a supervised machine learning model that is beneficial for solving classification problems [8]. It creates a line or hyperplane to categorize the data. So, it can correctly decide the category of new data. SVM classifiers provide good accuracy and perform faster prediction compared to K-NN by taking care of outliers. They use less memory. Next, K-NN is one of the most straightforward supervised ML algorithms. It does not make any assumption on the underlying data. In K-NN, the similarity is the basis for classifying the new data. It is very robust for noisy training data. It always incorporates the calculation of the K-value, which may be difficult for some cases. Further, Decision tree is also supervised machine learning algorithm where the data is divided according to a certain attribute. The tree consists of decision nodes and leaves.

.A Motivation

The work in this paper is motivated by the following major limitation in the existing literature.

- In existing work [9]–[13], there exists the use of multimedia Technology for the courses (e.g., Data structures, mathematics, Science, and English etc.). It does not incorporate multimedia teaching approach for engineering courses and not used any ML model.
- The prior studies [12] includes use of multimedia technology for children to study basic mathematics skills, but does not consider the professional students and career oriented courses as well as not having any consideration of ML model.
- The previous work [14] makes use of a computer assisted instruction package which is a part of multimedia technology. This work is not using the complete multimedia technology and ML model.
- The existing work [15] incorporates multimedia computer games for visually disabled students and eluded the professional students. In [16], multimedia technology used for children with autism and excluded the professional learners and machine learning algorithm.
- In the previous work [17], there exists the use of Multimedia technology for summer students and not for all admitted students and not used ML models. In [18], the use of Multimedia educational program is for science achievement of middle-school students excluding junior, senior and professional students as well as not considered any machine learning model.

In this paper, we address the problem: *how to identify which teaching methodology is better for third year, semester-VI, and Mechanical Engineering students on labeled dataset for assessment of the course Energy Conversion-1? and Develop the Result prediction system using SVM, K-NN and decision tree models and compare them.* To give solution to this problem, this work proposes multimedia technology, such as virtual lab, Google classroom, learning management system (LMS), power point presentations, You tube videos for teaching by the faculty. In addition, we developed the result prediction system for the same students using ML algorithms and compared to decide which model is the best for our data.

.B Major Contributions

To the best of our awareness, this is the first endeavor for addressing the problem of identifying which teaching methodology is better for the course Energy Conversion-1 of third year, semester-VI, Mechanical Engineering students using statistical technique on labeled dataset and developing the result prediction system and comparing them. This paper makes following major contributions:

- We propose a technique to know how multimedia teaching methodology help in improving pedagogical quality of teaching in a classroom in the course Energy Conversion-1.
- This work proposes the study of the significant difference in the process of classroom teaching through traditional method and classroom teaching through multimedia technology for professional students of Engineering.
- Next, this work proposes not only partial use of multimedia technology but also the various forms of multimedia technology.
- Further, this work also proposes to find out academic achievement of students in Energy Conversion-1 subject by teaching them in conventional method and by using multimedia technology.
- Next, this work proposes the development of the result prediction system using SVM, K-NN, Decision Tree machine learning algorithms and compares which model gives better accuracy for our data.

The rest of paper is organized as follows. Next section illustrates the terminologies used in this research work. Section III proposes t-test statistical technique for identifying better teaching methodology for students and the implementation of student result prediction system using SVM, K-NN and Decision Tree machine learning algorithms and comparison of them to decide which gives better accuracy for our dataset. In Section IV, we discuss the mechanisms of collecting dataset from the assessment of students. Next, Section V presents the experimental analysis of proposed approach. Finally, the paper is concluded in Section VI, with its future scope.

.II. Preliminaries and Problem Statement

In this section, we first describe the different terminologies used in this work. Later, this section covers a brief description of the problem associated with teaching methodology identification for students and the overview of solution.

.A *Preliminaries*

The proper teaching method for the students can be identified by analyzing the results of different examinations such as Test-1, Test-2 and End Semester Examination for the same course taught by the same faculty with different teaching methodologies.

Definition 1 (Multimedia). *The basic concept of Multimedia stands for computer controlled integration of more than one continuous media, such as audio, text, graphics, images, animation, and video which can present the information in a structured manner as well as store, process and transmit all information to the user digitally [19].*

Definition 2 (Learning Process). *Learning Process incorporates interactive components, such as attention, memory, language to interact not only with each other, but also with classroom climate, social skills, behavior, and teachers to acquire change in existing knowledge to achieve specific goals [20].*

Definition 3 (Educational (Learning) Technology). *Educational (Learning) Technology is integrating the computer hardware, software and professional knowledge from several areas, such as mechanical, electronics, computer science etc. and provides practice to facilitate learning in order to improve academic performance [21].*

.B *Problem statement and overview of the solution*

Proper teaching methodology identification in the education helps in increasing the enthusiasm of students in learning different courses, as explained in the introduction. The instances of data are collected from the assessment of Test-1 and Test-2 of the course Energy Conversion-1 of third year, semester VI, Mechanical Engineering students for different academic years, namely 2016-17 and 2018-19. This work, therefore, addresses the problem of which teaching methodology is better for enhancing the learning capability of students. Next, this work concentrates on the design of result prediction system.

Overview of the solution: This work proposes a statistical technique that uses the concept of t-value which proves that the multimedia teaching methodology is better than the black board and chalk traditional teaching methodology. The approach first calculates mean, standard deviation of Test-1 of the course Energy Conversion-1 for two different academic years, namely 2016-17 and 2018-19, where the faculty used different teaching methodologies, such as conventional black board method and multimedia teaching methodology respectively. Next, the approach calculates mean, standard deviation of Test-2 of the course Energy Conversion-1 for two different academic years, namely 2016-17 and 2018-19, where the faculty used different teaching methodologies, such as conventional black board method and multimedia teaching methodology respectively. Later, the calculated values are used to find t-value. Further, t-value is used for taking the decision which teaching methodology is better. Finally, it is concluded that the multimedia teaching methodology is better with 0.05 level of significance in the course Energy Conversion-I. Next, in the implementation of student result prediction system, the model learns from the training data and predicts result for the test data. We have developed three result prediction system using three machine learning algorithms, namely, SVM, K-NN and Decision Tree. After that we have compared which is the best suitable model for our dataset.

.III. Proposed Approach

a) Computerized Morse Test Setup. b) Software Based Gas Analyzer.

c) Double Cylinder Diesel Engine. d) IC Engine Lab.

Fig. 3: Multimedia based experiments conducted in lab for EC-1.

In this section, we propose a multimedia based learning approach for assessment of students. Fig. 3 illustrates wellequipped Multimedia classroom cum lab used for Energy Conversion-1. Part (a) of fig. 3 shows the Morse test setup which incorporates the computer software used as Multimedia digital tool. This helps to the students to empower their thinking to analyze various engine parameters, such as, speed, load, torque, and indicated power etc., Here, the student can apply load on the engine shaft electronically during performance of the experiment. With the help of well equipped control panel attached with the engine, the student can also adjust the speed of the engine shaft electronically. Finally, after performing the experiment, the students get the numerical as well as graphical results on the computer screen. This result preparation takes place automatically with the help of software tool. Next, part (b) of fig. 3 shows the exhaust manifold of diesel engine assisted with the software based exhaust gas analyzer applied as Multimedia digital tool creates interest in students for learning the emission levels of various exhaust gases. The exhaust gas from the diesel engine is fed to the software based exhaust gas analyzer. The analysis has been done and the output readings are shown on the device screen.The output readings include the amount of oxygen (O_2), the amount of unburned hydrocarbons (UBHC), the amount of NO_X and the amount of carbon monoxide (CO) present in the gas. With the help of these readings, it is possible to decide the emission level of the engine exhaust.

Further, part (c) of fig. 3 shows Multimedia incorporated digital control panel combined with two cylinder diesel engine setup help students to solve problems on brake power, indicated power, mechanical efficiency, and thermal efficiency etc., resulting in student team building. During performance of the experiment, the students do not require to apply load on the diesel engine manually. With the help of digital means, they can apply the required load on the engine. The students are able to adjust the speed of the engine electronically with the help of well-equipped control panel attached with the engine. Finally, as shown in Part (d) of fig. 3, Multimedia equipped internal combustion engine laboratory enhances analytical, technical skills of the students, and increases the enthusiasm of the students for learning a core course Energy Conversion-1. In Energy Conversion-1 laboratory, most of the experiment set ups are attached with well-designed digital control panel and some of the experiment set ups are attached with software based devices or computers.

This paper comprises the research work which considers the results of the engineering students for the same subject for two different academic years. For one of the academic year, the teaching methodology includes multimedia based approach. The other academic year incorporates the use of the traditional teaching methodology, such as only blackboard teaching method. Here, we considered two different exams such as, Test-1 and Test-2 of the same subject.

1) Population and Sample: This research incorporates Third year, Mechanical Engineering, Semester-VI class of two different academic years. The total count of the students in this two different academic years appeared is 75.

2) Evaluation of exams for comparison: In this section, the continuous evaluation of the students in Test-1, Test-2 and ESE for the academic year, 2018-19,to evaluate their achievements in the the course Energy Conversion-1 of Semester-VI.

. IV. DATA COLLECTION

In this section, we will discuss the whole procedure used for data collection. The assessment of Test-1, Test-2 and ESE for third year students prepared by the course faculty was governed on the students of academic year, 2016-17 to assess their achievement in Energy Conversion-1.

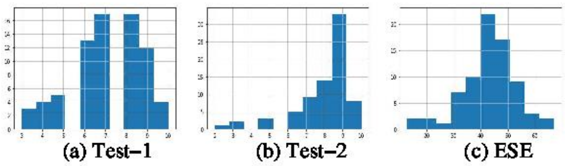
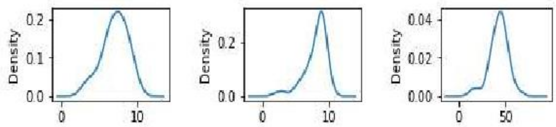


Fig.4: Histogram of Assessment of Test–1, Test–2 and ESE in EC–1.

Fig. 4 illustrates the histogram of assessment of the students in Test-1, test-2 and ESE. Fig. 5 illustrates the density graph of assessment of the students in Test-1, test-2 and ESE. Fig. 6 illustrates the scatter plot of assessment data for Test-1, Test-2 and ESE of Energy Conversion-1.



(a) Test−1 (b) Test−2 (c) ESE

Fig.5: Density graph of Assessment of Test−1, Test−2, ESE in EC−1.

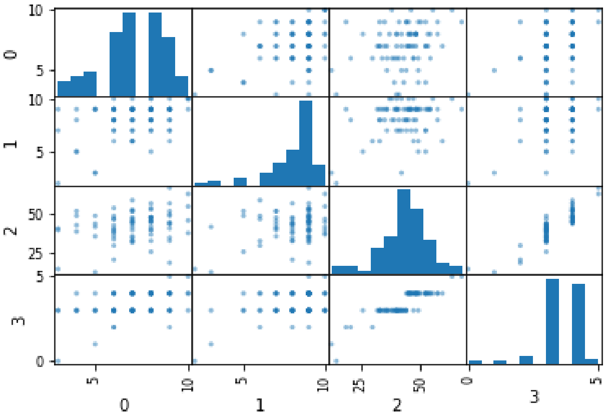


Fig. 6: Scatter plot of data.

.V. *EXPERIMENTS AND RESULTS*

In this section, several comparisons are performed to decide the best suitable model for the result prediction by providing answers to the following questions:

Finally, this section presents a comparative analysis of the proposed approach. Fig. 7 illustrates the number of students under the different levels of assessment of Test-1 in the course Energy Conversion-1 for different academic years with multimedia and without multimedia teaching methodology for 75 students.

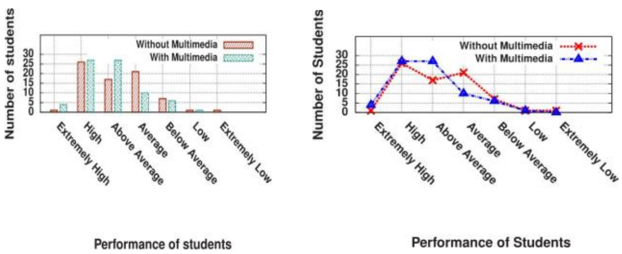


Fig. 7: Test-1 Assessment of Energy Conversion-1.

As shown in the Fig. 7, the analysis for Test-1 observation shows that there is a significant change in the assessment of Extremely High, High, and Above average students by adopting the multimedia teaching method for academic year 2018-19.

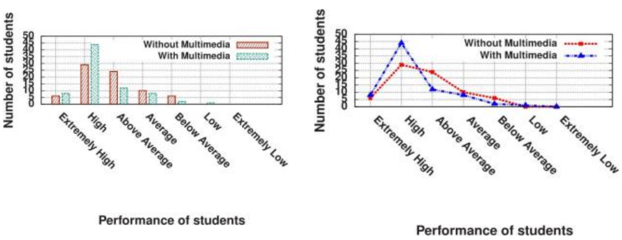


Fig. 8: Test-2 Assessment of Energy Conversion-1.

Next, Fig. 8 illustrates the number of students under the different levels of assessment of Test-2 in the course Energy Conversion-1 for different academic years with multimedia and without multimedia teaching methodology for 75 students.

As shown in the Fig. 8, the analysis for Test-2 observation shows that there is a significant change in the assessment of Extremely High, High, and Low students by adopting the multimedia teaching method for academic year 2018-19.

.A*Experimental Results*

In this section, statistical techniques are applied to assess the achievement of the proposed approach and provide answer to the following question: Whether by adopting multimedia teaching methodology for Energy Conversion-1 course of third year, Mechanical Engineering, Semester-VI students, the overall learning capability of the students improved or not?

TABLE I: t-value for Test-1 with different teaching methodology

Name of Exam	Count	Mean	S.D.	t-value	Remark
Test-1 With Multimedia	75	20.45	5.22	1.82	Significant
Test-1 Without Multimedia	75	18.66	6.01		

Table I gives information about the type of exam with teaching methodology, number of students, mean, and standard deviation of the Test-1. As shown in Table I, t-value for assessment of Test-1 for two academic years, used different teaching methodologies is 1.82. This value is statistically significant at 0.05 level of significance. Thus, there exists a significant improvement in Test-1 of Energy Conversion-1 course of students when instructed through multimedia technology.

TABLE II: t-value for Test-2 with different teaching methodology

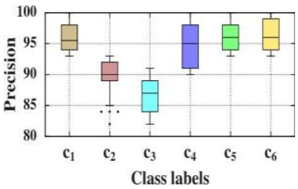
Name of Exam	Count	Mean	S.D.	t-value	Remark
Test-1 With Multimedia	75	23.21	4.85	2.62	Significant
Test-1 Without Multimedia	75	21.01	5.29		

Table II gives information about the type of exam with teaching methodology, number of students, mean, and standard deviation of the Test-2. As shown in Table II, the t-value for assessment of Test-2 for two academic years, used different teaching methodologies is 2.62. This value is statistically significant at 0.05 level of significance. Thus, there exists a significant improvement in Test-2 of Energy Conversion-1 course of students when instructed through multimedia technology. Therefore, it is concluded that the multimedia teaching methodology is effective as the students scored better in Test-1 as well as in Test-2 in comparison to the conventional teaching methodology.

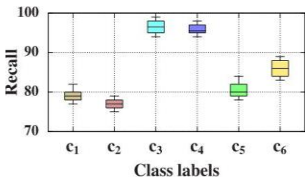
Additionally, the ESE result prediction system developed using SVM, K-NN, and Decision tree ML algorithms and compared to answer the following question: Which ML model predicted the student ESE result more accurately?

- What is the precision and recall performance measures during training and testing by using K-NN? (Section V-A1)
- What is the precision and recall during training and testing by using SVM? (Section V-A2)
- What is the precision performance measure and recall during training and testing by using Decision Tree? (Section V-A3)
- Which is the best model for our data? (Section V-A4)

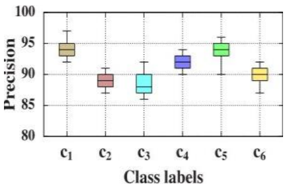
1) Precision and recall of K-NN: This work evaluates the precision and recall of the K-NN approach using ESE exam result dataset and achieved outcomes are shown in Fig. 9. The first six (6) categories in the ESE exam result dataset are represented by c_1:Extremely High, c_2:High, c_3 :Above Average, c_4:Average, c_5:Below Average, and c_6:Low. We considered the first six categories as the last category incorpotrates very less number of data instances. Part (a) of Fig. 9 shows that precision performance measure of c_5 category is maximum, and the recall performance measure of category c_3 attains to the highest, as given in part (b) of Fig. 9. The fact that the existence of



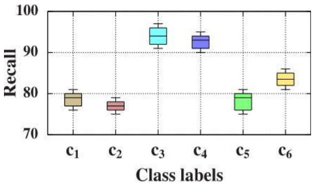
a) Training Precision of K-NN



b) Training Recall of K-NN



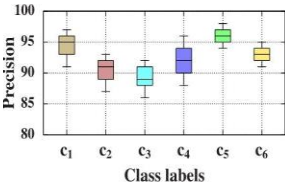
c) Testing Precision of K-NN



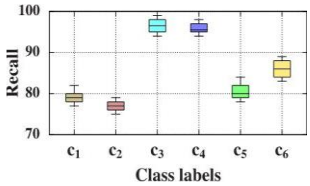
d) Testing Recall of K-NN

Fig. 9: Precision and recall performance measure on training and testing ESE Exam result dataset using K-NN.

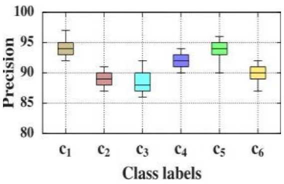
unequal data instances across different categories in the dataset is indicated by the variousness in the value of precision and recall performance measures. The unequal instances are due to the similar marks. Similar, outcomes are achieved for testing data as shown in parts (c) and (d) of Fig. 9. The precision performance measure of category c_1 and c_5 is approximately same for testing data and is maximum. The recall performance measure for category c_3 in testing has displayed similar tendency to that of training. These outcomes show that the KNN approach captures the class imbalance problem in the dataset and achieves the performance around 70%. The recall performance measure for category c_3 in testing has displayed similar tendency to that of training. These outcomes show that the KNN approach captures the class imbalance problem in the dataset and achieves the performance around 70%.



a)Training Precision of SVM.



b) Training Recall of SVM.

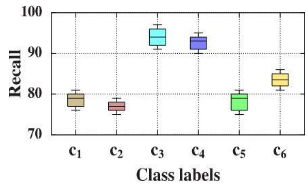


c) Testing Precision of SVM .

d) Testing Recall of SVM.

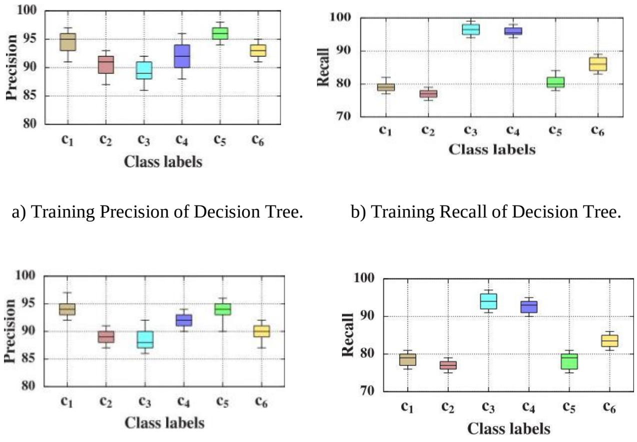
Fig. 10: Precision and recall performance measure on training and testing ESE exam result dataset using SVM.

2)*Precision and recall of SVM:* This work evaluates the precision and recall of the SVM approach using ESE exam result dataset and achieved outcomes are shown in Fig. 10. The six (6) categories in the ESE exam result dataset are represented by c_1 , c_2 , c_3 , c_4 , c_5 , and c_6 . Part (a) of Fig. 10 shows that the precision performance measure of c_5 category is maximum, whereas the recall performance measure of category c_3 attains to the highest, as given in part (b) of Fig. 10. The existence of the



unequal instances present in the various categories in the data is shown by the heterogeneousness in the value of the precision and recall. The disproportion of theinstances is due to the same marks. Similar, outcomes are achieved for testing data as given in parts (c) and (d) of Fig. 10. The precision performance measure of category c_1 and c_5 is approximately equal for testing data and is maximum among all. The recall for category c_3 in testing has displayed similar tendency to that of training. These results show that the SVM approach captures the class imbalance problem in the dataset and achieves excellent performance around 78%.

3) Precision and recall of Decision Tree: This work evaluates the precision and recall of the Decision Tree approach using ESE exam result dataset and achieved outcomes are shown in Fig. 11. The six (6) categories in the ESE exam result dataset are represented by c_1, c_2, c_3, c_4, c_5, and c_6. Part (a) of Fig. 11 gives that the precision performance measure of c_5 class is maximum, and the recall performance measure of class c_3 attains to the highest, as given in part (b) of Fig. 11. The fact that, there



a) Training Precision of Decision Tree. b) Training Recall of Decision Tree.

c) Testing Precision of Decision Tree. d) Testing Recall of Decision Tree.

Fig. 11: Precision and recall performance measure on training and testing ESE exam result dataset using Decision Tree.

exists unequal data instances in the various classes in the dataset is represented by the variousness in the value of the precision and recall. The asymmetry of the instances is due to the same marks. Similar, outcomes are achieved for testing data as shown in parts (c) and (d) of Fig. 11. The precision performance measure of category c_1 and c_5 is approximately equal for testing data and is maximum among all. The recall performance measure for category c_3 in testing has displayed similar tendency to that of training. These outcomes show that the Decision Tree approach captures the class imbalance problem in the dataset and achieves excellent performance around 70%.

4) *F1-score and Accuracy of K-NN, SVM and Decision Tree:* Further, this work studies the F1-score and Accuracy of result dataset using K-NN, SVM and Decision tree approaches. Let, K − NN, SVM, Decision Tree denotes the approaches respectively. Fig. 12 illustrates the F1-score and Accuracy of three classifiers.

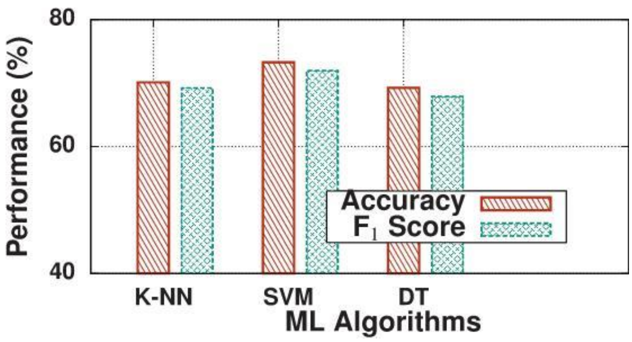


Fig. 12: F1-score and Accuracy of three ML algorithms.

.VI. CONCLUSION

In this research paper, we proposed a multimedia based teaching approach that uses Google classroom, Learning Man-agement System (LMS), virtual lab, audio, video, animations, PowerPoint presentations, YouTube, and digital lab. Here, for the academic year 2016-17, the faculty used the traditional teaching methodology for the course Energy Conversion-1 and for the academic year 2018-19, the same faculty used the Multimedia teaching methodology for the same course. This work proposed t-value statistical calculation for comparison of teaching methodologies which proves multimedia based teaching approach is better than traditional. Moreover, we also implemented ESE result prediction system using SVM, K-NN, and Decision tree ML models and compared the accuracy, F1 score, precision and recall of three algorithms. The SVM, K-NN and Decision Tree model predicted the ESE result with 78%, 70% and 70% accuracy, respectively. The comparison showed that the SVM model predicted the ESE result with 78% accuracy. Therefore, SVM is the best classifier for our data. This work also gives a future research direction towards inclusion of deep learning model for prediction of the ESE exam result.

Acknowledgment

In this section, we would like to acknowledge the con-tinuous motivation, support from the management, principal, and department for the innovative practices. We would like to thank them for providing Multimedia infrastructure to make the teaching learning process better. We would also like to acknowledge the participation of faculty who has directly or indirectly contributed in the preparation of the course content and in the execution of the various activities related to it.

REFERENCES

A. M. Eskicioglu and D. Kopec (2003). The ideal multimedia-enabled classroom: Perspectives from psychology, education, and information science. *Journal of educational multimedia and hypermedia, vol. 12, no. 2, pp. 199–221.*

A. Joshi (2012). Multimedia: A technique in teaching process in the classrooms. *Current World Environment, vol. 7, no. 1, p. 33*.

M. Neo and K. T. Neo (2001). Innovative teaching: Using multimedia in a problem-based learning environment. *Journal of Educational Technology & Society, vol. 4, no. 4, pp. 19–31.*

A. Azemi (1996). Using multimedia courseware in engineering education. *Technology-Based Re-Engineering Engineering Education Proceedings of Frontiers in Education FIE'96 26th Annual Conference, vol. 1. IEEE, pp. 209–212.*

J. A. B. Grimoni, L. Belico dos Reis, and R. Tori (1998). *The use of multimedia in engineering education–an experience*.

S. Malik and A. Agarwal (2012). Use of multimedia as a new educational technology tool-a study. *International Journal of Information and Education Technology, vol. 2, no. 5, p. 468.*

A. Gunasekaran, R. D. McNeil, and D. Shaul (2002). E-learning: research and applications. *Industrial and commercial training.*

D. Kuvcak, V. Juric, and G. Djambic (2018). Machine learning in education-a survey of current research trends. *Annals of DAAAM and Proceedings, vol. 29.*

S. Junaidu (2008). Effectiveness of multimedia in learning and teaching data structures online. *Turkish Online Journal of Distance Education, vol. 9, no. 4, pp. 97–107.*

G. P. Joshi, S. Jha, S. Cho, C. Seo, L. H. Son, and P. H. Thong (2020). Influence of multimedia and seating location in academic engagement and grade performance of students. *Computer Applications in Engineering Education, vol. 28, no. 2, pp. 268–281.*

H.-C. She and Y.-Z. Chen (2009). The impact of multimedia effect on science learning: Evidence from eye movements. *Computers & Education, vol. 53, no. 4, pp. 1297–1307.*

S. Nusir, I. Alsmadi, M. Al-Kabi, and F. Sharadgah (2013). Studying the impact of using multimedia interactive programs on children's ability to learn basic math skills. *E-learning and Digital Media, vol. 10, no. 3, pp. 305–319.*

S. Thamarana (2015). Role of multimedia resources in teaching and learning of english language. *Teaching English Language and Literature: Challenges and Solutions, pp. 187–192.*

A. Deshpande (2010). Use of educational technology in engineering education–a computer assisted instruction (multimedia) package for engineering students. *WSEAS Transactions on Advances in Engineering Education, vol. 7, no. 8, pp. 245–254.*

A. Buaud, H. Svensson, D. Archambault, and D. Burger (2002). Multimedia games for visually impaired children. *International Conference on Computers for Handicapped Persons. Springer, pp. 173–180.*

E. I. Konstantinidis, M. Hitoglou-Antoniadou, A. Luneski, P. D. Bamidis, and M. M. Nikolaidou (2009). Using affective avatars and rich multimedia content for education of children with autism. *Proceedings of the 2nd international conference on pervasive technologies related to assistive environments, pp. 1–6.*

T. Murphy (2007). Williams instructional technology: summer students working on faculty projects. *Proceedings of the 35th annual ACM SIGUCCS fall conference, pp. 272–276.*

N. G. Murray, K. A. Opuni, B. Reininger, M. N. Sessions, M. M. M. Mowry, and M. Hobbs (2009). Multimedia educational program increases science achievement among inner-city non-asian minority middle-school students. *Academic medicine: journal of the Association of American Medical Colleges, vol. 84, no. 6, p. 803.*

H. Almara'beh, E. F. Amer, and A. Sulieman (2015). The effectiveness of multimedia learning tools in education. *International Journal, vol. 5, no. 12.*

B. Duckett (2003). Britannica concise encyclopedia. *Reference Reviews.*

R. C. Richey (2008). Reflections on the 2008 aect definitions of the field.