International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Machine Learning and Ai in Marketing–Connecting Computing Power to Human Insights

[1]Dr. Pooja Nagpal, [2]Dr. C. Vinotha, [3]Lucky Gupta,[4]Dr. Gunjan Sharma, [5]Dr. Khyati Kapil, [6]Vijay Kumar Yadav, [7]Akhil Sankhyan

Submitted: 06/02/2024 **Revised**: 14/03/2024 **Accepted**: 20/03/2024

Abstract: Researchers' interest in artificial intelligence (AI) agents that are driven by machine learning methods has been piqued as a result of the rapid changes that these technologies are creating in the marketing sector. In the framework of this article, we investigate and argue in favour of the use of methods related to machine learning to marketing research. We provide a comprehensive overview of the common aims and methodologies of machine learning and compare them to the traditional statistical and econometric approaches that are employed by marketing professionals. In this research, we claim that machine learning approaches can analyse vast volumes of unstructured data, make accurate predictions, and have model structures that are adaptable. In addition to being difficult to understand, these methodologies are also unclear with reference to the models. We provide scalable and automated decision support capabilities, which are essential for business managers. We investigate the most important business trends and practices that are being driven by AI, as well as academic marketing research that combines machine learning approaches. Most significantly, we provide both a detailed plan for further research as well as an extensive conceptual framework.

Keywords: *Artificial intelligence (AI), Machine learning, Business Managers, Marketing Sectors*

1. Introduction

Take a look at this diagram to get an idea of how the different phases of the buying process could play out for a consumer. Customers may be interested in reading devices for electronic books. She starts her hunt for an e-reader on Google, and then moves on to a few more websites to study the product details on each one before making a final decision. A few days later, when she is viewing movies on YouTube, she comes across an advertising for an electronic reader. Out of sheer curiosity, she navigates to the company's website, where she spends some time learning more about the offering while also making use of the live chat function to pose a few questions. After that, she reads through the feedback left by customers on a different website. When she browses the internet over the following few days, she is going to come across an overwhelming number of adverts for that electronic reader. After clicking the link, she makes a purchase, and then after that, she sends a confirmation email with a promo code attached to it. On Facebook, she discusses the product as well as her pleasant experience with it, and on Instagram, she posts a few photographs along with some quick comments about each of them. Her close friends have responded with a lot of excitement to the posts [1].

The consumer is completely unaware that automated technologies are responsible for managing a significant chunk of this journey. The search results are generated by an intricate algorithm that Google uses to determine rankings. This algorithm based part of the ranks on the bids that are placed by advertisers, and these bids are created automatically by software that bids on their behalf. The content of the websites is modified just for her based on the information in her profile via a process that is referred to as website morphing, and chatbots do react to her questions. Both the advertisements that she often encounters and the evaluations that she peruses are sent to her by retargeting algorithms that make use of read-time bidding. The evaluation methodology arrived at the conclusion that, given the importance of the reviews, it would be prudent to highlight them. At the appropriate time in the process, the pricing system of the company generates the coupon that gives her the individualised price. In order to gauge her disposition and response, social listening algorithms collect her tweets from a wide variety of social media networks and aggregate them. The

1Associate Professor, Department of Management Studies, International School of Business Excellence, (ISME), Bangalore, Karnataka, India
**pooja.nagpaal@gmail.com*
2Associate Professor, Department of MBA, Sri Krishna College of Engineering and Technology
Kuniamuthur, Coimbatore, India
cvinotha@gmail.com
3Assistant Professor, Raj Kumar Goel Institute of Technology, Ghaziabad
luckymalu@gmail.com
4Assistant Professor, Institute of Business Management, GLA University, Mathura
**gunjan.sharma@gla.ac.in*
5Associate Professor, Department of Management Studies, Graphic Era (Deemed to be University), Dehradun
khyatikapil.mgt@geu.ac.in
6Lloyd Institute of Engineering & Technology, Greater Noida
vijay.yadav@liet.in
7Lloyd Law College, Greater Noida
akhil.sankhyan@lloydlawcollege.edu.in

term "artificial intelligence" (AI) refers to these computerised systems that are able to make split-second judgements that are based on the surrounding environment. AI agents is yet another name for what we often refer to as artificial intelligence. Techniques from contemporary machine learning are often used during the construction of artificial intelligence agents [2].

Since the 1990s, the major emphasis of artificial intelligence research has been on the development of algorithmic frameworks for machine learning. According to the definition that was presented by Mitchell (1997), a computer programme "learns from experience E" in regard to a certain group of tasks known as T and a performance measure known as P "if its performance at tasks in T, as measured by P, improves with experience E." Provided below is the category of activities denoted by the letter T, which this definition applies to. This definition refers to situations in which the computer program's performance improves as a result of increased exposure to the specified experience. Although it was created separately at first, machine learning is currently the predominant paradigm in research on artificial intelligence and is often recognised as a subfield of AI. This is despite the fact that it was first developed as an independent process. In the last 10 years, significant improvements in the performance of artificial intelligence have been achieved in a broad variety of domains. These improvements have been made in many areas that were formerly assumed to need the intellect of humans, such as autonomous driving, voice recognition, picture identification, and a great many other areas. The introduction of large quantities of data, the exponential development in processing power, and other approaches that make use of numerous levels of representation and are often implemented with neural networks that have many hidden layers are primarily responsible for this feat. Because of this advancement, the scope of applications for which other machine learning approaches may be used has broadened [3].

During the last 20 years, artificial intelligence has had a substantial influence on a wide variety of different industries, including biology, education, engineering, finance, and healthcare, to name just a few of these sectors. When it comes to marketing, this dictum also holds true. The quantity of digital traces that are left behind has greatly risen as the level of personalization and pervasiveness in both consumer and commercial connections has increased. As a direct response to the quantity of data, a lot of businesses have made considerable investments in machine learning systems in an effort to improve their marketing abilities. According to projections made by BCC Research, the market for solutions that are enabled by machine learning will be worth $8.8 billion by 2022 and will expand at a pace of 43.6% annually3. All of these technologies are powered by extremely complex machine learning algorithms, such as deep learning engines, which analyse and tag the billions of images hosted on social media sites like Facebook; automated bidding algorithms, which analyse a web surfer's profile in milliseconds to determine the best bid for ad delivery; chat bots, which converse with users in a way that is reminiscent of human conversation; and automated neural networks (ANL), which use degenerative neural networks. These applications, along with a large number of others, such as analysis of customer sentiment, prevention of customer churn, and mining of social media, have demonstrated the efficacy of artificial intelligence agents powered by machine learning algorithms in the processing of enormous amounts of unstructured data in real-time and the production of accurate predictions to aid in the making of marketing decisions. These agents are able to process the data in real-time and produce accurate predictions to aid in the making of marketing decisions. As a direct result of implementing these strategies, the level of productivity at the organisation has dramatically improved [4].

We provide a comprehensive analysis, including a commentary that looks to the future, of the various machine learning strategies that were investigated in this research. In the first step of this process, we are going to present an overview of several typical machine learning solutions for addressing these obstacles. Active learning, transfer learning, reinforcement learning, unsupervised learning, semi-supervised learning, and supervised learning are some of the approaches that fall under this category. Statistical and economic models may be used to analyse large volumes of unstructured data; however, technologies connected to machine learning are more effective at doing so. In addition to this, they provide adaptable frameworks that can come close to approximating difficult functions, resulting in outcomes that may be predicted with relative ease. On the other hand, the algorithms that are used in machine learning often lack intuitive interpretation, especially at the causal level. It is also uncertain at this moment if these methods are able to capture the heterogeneity and dynamism at the level of the individual client. This is something that needs to be investigated. This is necessary for the generation of predictions by machine learning algorithms, which need a significant amount of data. After that, we'll go over a couple other issues that are just as significant [5].

The whole shopping experiences of customers are receiving an increasing amount of attention from commercial enterprises. In order to do this, significant, automated, context-dependent personalization and targeting must be performed, in addition to the maintenance of regular, media-rich connections with customers. Artificial intelligence is responsible for these technological advancements. These trends stimulate and push the development of machine learning methods that are continually improving, hence producing a positive feedback loop that is revolutionising all aspects of marketing practises. This loop is creating a positive feedback loop that is revolutionising all aspects of marketing practises. This cycle is producing a positive feedback loop that is fundamentally altering the way marketing is carried out. Next, we take a look at the relatively new but rapidly growing body of literature that is dedicated to the use of machine learning in the field of marketing.

When compared to the data that was utilised to construct a machine learning model during the technical analysis, the data that was used for the basic analysis consisted mostly of unstructured information that was difficult to understand. However, a number of studies that used this form of study have demonstrated that it has the potential to produce a rational prediction of the market price. These studies were carried out by a number of different researchers. On the other hand, in order to carry out a technical analysis of the market, one has just to have access to historical price information. These statistics are now available to the general public and are presented in a style that is easily arranged. As a direct consequence of this, a much greater number of research papers that investigate stock market forecasting using technical analysis approaches have appeared as a direct outcome. One of the first endeavours in this field was the development of a feed-forward neural network (NN) algorithm in the beginning of the 1990s. This was one of the early endeavours in this area. This method was designed to anticipate the stock market by using past financial data, such as interest rates and exchange rates. Their model served as a tool for decision-making at every stage of the process, from generating the signal to buy or sell firm shares to analysing the results of such actions. In spite of the fact that their model had the potential to be profitable for the buy-and-hold strategy, it was unable to reliably predict the selling signal. Several different machine learning approaches, including as artificial neural networks (ANN), random forests (RF), "support vector machines" (SVM), and naive Bayesian, were investigated in order to determine the extent to which machine learning is able to make accurate predictions when applied to technical data. In order to find a solution to this problem, we investigated and experimented with four distinct machine learning (ML) approaches: naive Bayesian, "support vector machine" (SVM), random forest, and artificial neural network (ANN). According to the results of a testbed that was carried out over a period of ten years, the technique of random forests may be more effective than other approaches, especially when the input data is discretized. This was the conclusion reached after the testing was carried out. In more recent study, the problem of predicting the daily return of the stock market was approached by using machine learning, which included using a comprehensive big data analytical procedure. Deep neural networks (DNN) and artificial neural networks (ANN) were used to fit the model and generate predictions. The model included sixty different financial input characteristics, and the DNN and ANN were trained on those characteristics. They drew the conclusion that the ANN performed better than the DNN and that the use of principal component analysis (PCA) during the pre-processing stage has the potential to increase the accuracy of prediction.

2. Review of Literature

Due to the quick changes that these technologies are bringing about in the corporate sector, researchers are exhibiting an increased interest in artificial intelligence (AI) agents that are powered by machine learning algorithms. Within the confines of this article, we analyse and make a case for the use of techniques associated with machine learning in the arena of marketing research. In this section, we present an overview of the typical aims and tactics of machine learning, and we contrast them with the usual statistical and econometric techniques that are utilised by marketing experts. In this article, we claim that machine learning techniques have flexible model structures, the capacity to analyse vast amounts of unstructured data, and the ability to produce correct predictions. These three capabilities set machine learning approaches apart from other methods of data analysis. It's possible that these procedures are difficult to grasp and don't provide clear information on the models. In this research, the most significant AI-driven commercial practises and trends are investigated. The study also contains a literature assessment of academic marketing literature that makes use of machine learning methods. In addition to providing a comprehensive conceptual framework for the work that will be done in the future, the most important contribution that we provide is that we outline a detailed research agenda for the work that will be done in the future. We propose a number of research priorities, some of which are as follows: expanding machine learning methods and utilising them as crucial components in marketing research; utilising the methods to draw conclusions from substantial amounts of unstructured, tracking, and network data; utilising the methods in a transparent manner for descriptive, causal, and prescriptive analyses; and utilising the methods to represent customer purchase journeys. These priorities are derived from the five primary aspects that make up this kind of study, which are the technique, data, use, and application of empirical marketing research. We have every confidence that the exhaustive study plan that we have prepared will stimulate more research into this fascinating topic. In the field of marketing, using strategies that are founded on the concept of machine learning is an option for a diverse variety of contexts [6].

A revolution in marketing strategies is now taking place as a result of a number of variables, two of which are the proliferation of data provided by customers and the growing accessibility of machine learning (ML) technology. Researchers and company marketers do not yet have a comprehensive knowledge of the myriad of opportunities presented by machine learning applications for the creation and upkeep of a competitive business advantage. Based on an exhaustive review of the relevant academic and industry literature, we provide in this study a taxonomy of machine learning use cases in marketing that we suggest. Our categorization system relies heavily on this study as its cornerstone. We have identified eleven use cases that are used often and have arranged them into four unique categories. These categories correlate to the main marketing-related machine learning leverage points of customer behaviour, consuming experience, decision-making, and financial consequence. We go over the recurring patterns of the taxonomy and give a conceptual framework for understanding and expanding it, with the primary emphasis being on the practical ramifications that it has for academics as well as marketers [7].

The authors propose a three-step process for strategic marketing planning, which makes use of some of the benefits that artificial intelligence (AI) has to offer. This marketing tactic is intended to be used in conjunction with more traditional marketing approaches. Some of the benefits of using artificial intelligence include the automation of mundane and time-consuming marketing duties via the use of mechanical AI, the analysis of data and the formulation of choices through the use of thinking AI, and the observation of social interactions and emotions through the utilisation of feeling AI. This framework provides an explanation of the possible applications of artificial intelligence in marketing research, strategy segmentation, targeting, and positioning, as well as STP and activities. During the phase of marketing research known as "market research," artificial intelligence may be used in a number of ways, including mechanical, thinking, and emotional AI [8]. These approaches may be utilised in order to gather data, evaluate markets, and get a better understanding of customers. Using AI may be the means through which these goals may be accomplished. While developing the STP for the marketing strategy, it is possible to use mechanical AI to reveal numerous segmentation categories. This may be done in parallel with the development of the STP. One possible use of artificial intelligence is the use of thinking AI to propose segments, while another possible application is the use of feeling AI to place segments. During the action stage of the marketing process, artificial intelligences that are mechanically driven have the potential to be utilised for standardisation, AIs that think have the potential to be used for personalising, and AIs that feel have the potential to be used for relationalization. These three types of artificial intelligence could work well together if they compliment one another. This paradigm is then applied to a variety of marketing disciplines, which are then grouped in accordance with the marketing 4Ps/4Cs, in order to demonstrate how AI may be strategically utilised [9].

3. A Basic Review of Machine Learning Jobs And Techniques

Machine learning by machine is a vast and rapidly expanding field that encompasses a number of techniques that may be used to the completion of a wide range of tasks. It is not possible to conduct a comprehensive review of the machine learning literature due to the constraints placed on the project by the requirements for the project. Instead, we will briefly go through a few common machine learning tasks and methodologies, all of which are likely to be helpful for academic marketing research. The whole image may be seen in Figure 1.

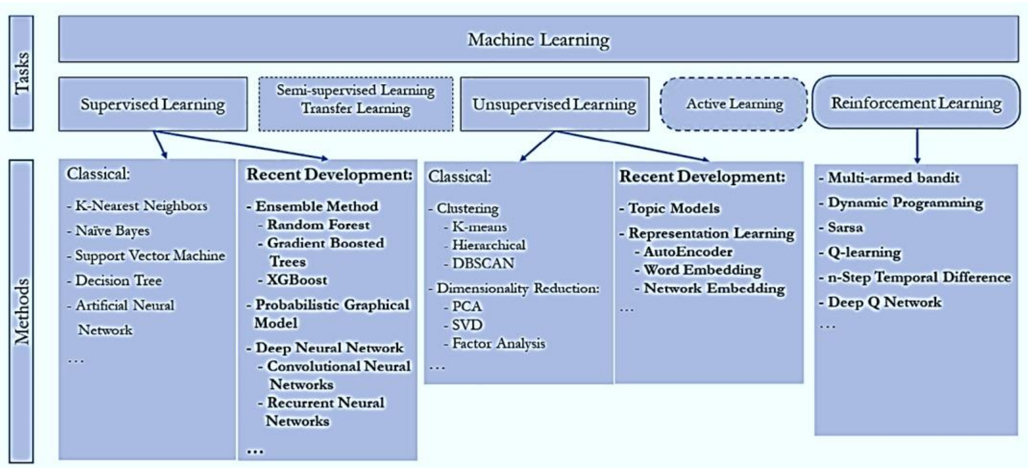

FIG 1: TASKS AND TECHNIQUES FOR MACHINE LEARNING.

❖ Machine learning tasks

In most cases, a machine learning algorithm will not take part in the process of gathering data; rather, it will evaluate an already existing dataset in order to accomplish a goal that has been determined in advance. In this model, supervised learning and unsupervised learning are the two primary task categories that comprise the total amount of work that has to be completed.

➢ *Supervised learning*

When performing tasks that need supervised learning, a training dataset is given in such a way that it is feasible to observe both the input, which is a collection of variables usually referred to as X, and the output, which is a target variable generally referred to as Y, for each occurrence of the task. This allows the task to be completed in a manner that meets the requirements of tasks that require supervised learning. This is accomplished by providing the dataset in such a way that makes it possible to view both the input and the output simultaneously [10]. Because of this, it is now able to carry out the task in an efficient manner.4 The purpose of supervised learning is to develop a function that can be used to the problem of predicting an output based only on its associated input. This is denoted by the equation $Y = f(X)$, and it is the primary objective of this kind of learning. The process that takes place when Y might either be a numeric or a categorical variable is referred to as regression or classification. Either word can be used to describe this process. The ability to make accurate predictions is the fundamental objective of supervised learning. Many researchers hold the view that it is more essential to develop a function that enhances the accuracy of output prediction from input rather than to figure out the "true" connection between the variables that are being investigated. Because there are no constraints placed on the model and memory may be utilised to achieve full accuracy for the training dataset, the accuracy of the prediction has to be evaluated using a distinct testing dataset in order to be properly evaluated. Make your model selections and/or hyperparameter adjustments with the help of this testing dataset. On the other hand, since it was taken into consideration when determining which models to use, the performance of the model that was selected is no longer an objective measure of how well it performs outside of the sample dataset. This is because it was taken into consideration when deciding which models to employ. This is because of the fact that it was taken into consideration when determining which models to employ, therefore it has come about as a consequence of that. As a consequence of this, the dataset used for training is often subdivided further into a training subset and a validation subset. After the models have been trained using the training subset, the validation subset will be used to choose the models that are the most successful or to adjust the models. This will take place before the models are deployed in production. After that, the performance of the most recently chosen model will have its functionality evaluated with the assistance of the testing dataset. The method of doing research known as cross-validation entails, among other things, using various subsets of the training dataset on many occasions for the purposes of both training and validation. This is done to ensure that the results of the training and the validation are comparable to one another.

➢ *Unsupervised learning*

When doing tasks that require unsupervised learning, the training dataset only includes the variables that are being input; the variables that define the output are either unknown or cannot be identified.5 Typical objectives of these kinds of endeavours include either gaining some kind of knowledge from the analysed data or finding previously undiscovered patterns in the data. These commitments come in a great number. Input instances are often segmented into a few different categories before being used in a clustering study. This helps to preserve the similarities that exist within groups while also highlighting the differences that exist across groups. The practise of turning data with a large number of dimensions into variables with fewer dimensions while maintaining the information contained in the original data is known as dimensionality reduction. In an unsupervised feature learning or representation learning task, features are extracted from the input data in order to represent those features. This may be done for either kind of learning. The method in question is one that is known as "representation learning." This process is known as representation learning. The extracted features include the most important information that was taken from the original data. These characteristics may either be evaluated or used as a jumping off point for more study, depending on what your goals are.

➢ *Active learning*

In the beginning stages of an active learning activity, there are not a lot of training examples accessible to choose from. The algorithm may add more training instances in order to improve the accuracy of its predictions; but, doing so results in more costs being incurred. The quantity of data that must be collected is going to be cut down while at the same time the accuracy of predictions will be improved. One of the primary purposes of active learning, which also includes a number of additional goals, is to identify the training environments that are the most important.

Making use of various incentives in order to encourage learning The learning agent engages in dynamic interaction with the environment while carrying out a task that requires reinforcement learning. It does so by taking action and keeping an eye on feedback in an attempt to improve its overall performance in relation to a certain objective function. Markov decision processes, which are more often referred to as MDPs, are extensively used in order to describe these actions. When marketing researchers employ dynamic programming models to examine probable future behaviour, MDPs are widely used as a framework to organise the data from such models. In order for the learning algorithm to acquire knowledge about the characteristics of the environment, it is necessary for it to choose the course of action that is most appropriate given the states. This area of machine learning concerns has lately garnered increased attention as a result of recent methodological advancements as well as an increasing number of commercial applications, such as morphing websites and driverless automobiles.

❖ Machine learning methods

There are numerous aspects of machine learning that are applicable to fields other than the one they were developed for. For example, logistic and linear regression are applied regularly in a wide variety of different sectors in addition to marketing, one of which is machine learning. Even while each field approaches its subject matter in a different way and has a distinct emphasis, the technical foundations are the same for all of them. In marketing research, the use of additional machine learning approaches, each of which is shown with a brief explanation below, is applied a smaller percentage of the time. Since this is such a broad subject, we will limit our discussion to the well-known supervised, unsupervised, and reinforcement learning algorithms that we consider to have a significant influence on marketing research. Instead, we are going to concentrate on the most recent events that have taken place in the region.

➢ *Methods for supervised learning*

approaches or procedures that are considered traditional. K-nearest neighbour, often known as KNN for short, is one of the instance-based approaches that is frequently used for the purpose of supervised learning. The constituent parts X1, Y1, and...Assume that the input will be Xi, the output will be Yi, and XN and YN will serve as the training examples. Before using KNN, one is need to first provide a distance metric that will be used all across the input space. After deciding which of the k training examples are the most similar to the test instances and have the shortest gaps between them, A prediction may be made by applying a function to these k instances, such as the weighted arithmetic mean of these k nearest neighbours. This will provide the forecast. This attribute has potential applications. The Bayes theorem, which asserts that $p(Y|X) = p(X|Y)p(Y)/p(X)$, is the foundation for the Naive Bayes (NB) approach, which is a classification method. NB is an abbreviation for "naive Bayes." The algorithm for classifying data using the Naive Bayes method is abbreviated with the letter NB. The Bayes classifier, which is theoretically valid, chooses the category that has the greatest posterior probability; nevertheless, it cannot be used in practise when applied to high-dimensional input vectors because of its inapplicability. Bayes classifiers pick the category with the highest posterior probability. By supposing that each input dimension is unrelated to the others, an NB classifier may speed up the classification process and simplify it to the estimation of a collection of uniform distributions. This can help the process become more manageable. In spite of the widespread belief, NB is effective and is used rather often, particularly in text mining. The maximum margin classifier that is referred to as “support vector machine” SVM, which stands for support-vector machine, is effective. When given a job that requires binary classification, the “support vector machine” (SVM) makes an effort to build a linear hyper plane in the input space that both maximises the margin of error and lies between the two classes. When linear hyper planes are inadequate, the “support vector machine” (SVM) may produce non-linear classification boundaries by transforming the main input space into higher dimensional spaces. This occurs when the “support vector machine” SVM is faced with an insufficient amount of data. In addition, a soft-margin “support vector machine” SVM not only allows for incorrect classifications but also penalises those who commit violations. “Support vector machine” SVM, which is by its very nature a binary classifier, may also be used for the categorization of more than two classes. To accomplish this goal, it is possible to train multiple binary classifiers that compare one variable to all the others or compare one variable to another. An solution that takes into account all classes at once is the use of modified procedures. Utilising a structured “support vector machine” SVM is yet another strategy that may be used to solve the problems that are caused by the presence of a large number of dependent variables. The use of “support vector machine” (SVMs) to regression issues is referred to as support-vector regression.

Random forests (RF) and gradient boosted trees (GBM) are two common ensemble approaches that make use of decision trees as base learners. The phrases "random forest" (RF) and "gradient boosted trees" (GBM) refer to these methods, respectively. It is common practise to refer to both RF and GBM by their respective acronyms. RF is used to generate one-of-a-kind trees, with bootstrap data taken from the primary data set serving as the sample. Only a random subset of the input variables is taken into consideration for each split in order to reduce the amount of correlation that exists between the results. The ultimate forecast is arrived at by RF by taking the estimations from a number of different trees and averaging them together. The GBM is used to train a number of trees in a sequential fashion. Following the implementation of the solutions found in previous trees, the number of errors in each subsequent tree is reduced. Techniques such as RF and GBM, which are both frequently used methods, are members of the class of strategies that have the greatest prediction performance. The sparsity-aware boosting approach of gradient trees was used in a significant number of the winning submissions to Kaggle's data science competitions. Because of recent developments in methodology, it is now feasible to employ tree ensembles as a tool for inferring the existence of causal linkages between events.

➢ ***Methods for unsupervised learning***

approaches or procedures that are considered traditional. A clustering method is used to the process of dividing the units into the different groups in order to emphasise both the differences between the groupings and the similarities that exist within them. After then, each of these collections is compared to every other collection. Typical methods include hierarchical clustering, which first allocates groups based on a random seed, then recalculates group means and reassigns them, and K-means, which initially assigns groups based on a random seed, then repeatedly combines similar groupings. Both of these methods regularly combine similar groupings. Hierarchical clustering begins by considering each unit as its own distinct group, and then continues to continuously join groupings that are related. K-means initially allocates groups based on a random seed. These two methods are used in the process of data clustering. DBSCAN is not affected by the impacts of data noise and can detect groups of any type. Dimensionality reduction may often be accomplished via the use of methods such as principal component analysis (PCA), singular value decomposition (SVD), and factor analysis (FA). As part of this process, the primary data, which had a high dimension, are transformed into variables that have a dimension that is smaller. Practises such as PCA, SVD, and FA are examples of common practises. Researchers in the area of marketing are familiar with these conventional methods since they have been used often in the field of machine learning as well as other disciplines of study.

the most current development and progress. It is possible for topic models to detect and extract latent semantic structures from text input because they use topics to transmit semantic information. This capability is made possible by the fact that topic models use topics. A text file may be conceptualised as a collection of themes, with each subject standing in for a different vocabulary distribution. Priors calculated using the Dirichlet technique are used in LDA, which is also known as Latent Dirichlet Allocation. This approach is used for mapping topics to words and documents to topics. Building on prior information retrieval techniques such as probabilistic latent semantic indexing (LDA), the original topic model was developed by using these methods as a foundation. After some time, this model would go on to become the most widely used example of its kind. There are accessible extensions that take into consideration the connection that exists between the topics or variables being studied. This strategy has been used in the field of marketing research to examine various forms of data that have relevant semantic patterns and to process textual data in the manner in which it was intended to be handled.

❖ **Advantages and disadvantages of machine learning techniques**

The statistical and econometric models that are so often used in quantitative marketing research are rather different from the approaches of machine learning that are now available to the general public. In order to save you time, we are going to briefly go through each of their individual benefits and drawbacks, which have been summarised in Table 1 for your convenience.

TABLE 1: THE ADVANTAGES AND DISADVANTAGES OF MACHINE LEARNING TECHNIQUES.

Strength	Capability to cope with data formats that are both organised and unstructured
	Having the ability to handle very large amounts of data
	Architecture based on adaptable models
	Great degree of accuracy in predicting
Weakness	Tough to grasp and comprehend
	It's more common for correlation to exist between two things than causation.
	Unproven in terms of analysing the dynamics and heterogeneity at the level of the individual consumer

➢ ***Advantages of machine learning techniques***

The capacity of machine learning algorithms to analyse data with complicated structures, such as large-scale network or tracking data, as well as unstructured data, such as text, image, audio, and video, is the first key strength of the technology. This ability allows the technology to analyse both structured and unstructured data. Due to the presence of this feature, the system is able to analyse both structured and unstructured data. This ability allows the technology to analyse both structured and unstructured data. Due to the availability of this capacity, machine learning can now evaluate both organised and unstructured input. In addition, the methods of machine learning may make use of data that is stored in a variety of hybrid forms, such as a combination of text, pictures, and structured data. The present boom in data has been driven almost entirely by unstructured data, which has increased the relevance of tactics that are based on machine learning.

Second, the methods of machine learning are capable of effectively managing a greater quantity of data than the econometric models are capable of. When applying econometric models, it is common practise to gather data on a sample size consisting of a few hundred or thousands of clients, with a restricted number of decision-making criteria. There is potential for much reduced sample sizes to be used in the development of predictive models. On the other hand, the field of study known as machine learning commonly makes use of larger datasets since it typically incorporates millions of separate observations. The use of efficient optimisation algorithms, such as stochastic gradient descent and parallel processing, makes it viable to train on large datasets. The implementation is made much easier by tools that are easily accessible and have high-performance computing capabilities. The ever-increasing volume of data that exists in the actual world necessitates, without a doubt, the use of scalable methods.

4. Research Methodology

Because of the many benefits that are offered by these methods, it is projected that the use of machine learning technology in academic marketing research would increase in the near future. Because this movement is still in its infancy, there is presently no consensus about the most effective technique to use when adopting these tactics, and there is no viewpoint that is all-inclusive because there has not yet been enough time for it to develop. In this part, we will outline a comprehensive study plan for you. The conceptual framework will serve as the jumping off point for our discussion, and after that, we will go into depth about each of the five primary pieces that comprise the conceptual framework. In addition, an overview of the research opportunities related with each trait is included in Table 2, which may be seen below.

TABLE 2: REQUEST FOR MACHINE LEARNING-BASED RESEARCH.

Aspect	Key research opportunities using machine learning methods
Method	For the purpose of marketing research, additional techniques, such as reinforcement learning, deep generative models, ensemble approaches, and PGM, should be presented, and the advantages of using them should be shown
	Bring methods of machine learning from the periphery towards the core, for instance by simulating the decisions that consumers make.
	The interpretability of machine learning algorithms should be improved, and statistical inference should be made possible, for example.
	Determine the extent to which the capabilities of the methodologies may be stretched.
Data	Make use of the methods for the analysis of unstructured data, in particular for audio and video.
	In order to draw conclusions, use the methodologies to the data gathered from monitoring the network and the consumers.
	Make use of the methods to conduct data analysis in a hybrid format, preferably in integrated models, and perhaps from a variety of sources.
Usage	Extend the usage of the algorithms for feature extraction and prediction and make them more effective.
	Adapting the research methodology for correlational, causal, and prescriptive investigations can help improve transparency and theoretical coherence.
	Investigate the degree to which each method works well for correlational, causal, and prescriptive research.

Issue	Utilise these strategies to create a buyer journey map, paying special attention to the early stages of the process.
	Utilising these methodologies, it is possible to create automated online decision-support capabilities for a variety of marketing operations.
	Utilise the tools and data provided by the platform in order to conduct market structure analysis.
Theory	the incorporation of human judgement into various machine learning approaches
	Maintaining coherence between perspectives informed by theory and those informed by data
	Investigate the theoretical basis of machine learning methods as well as the consequences they have.
	Analyse the potential outcomes that might result from companies using AI technology.

❖ **Introducing additional methods**

The field of machine learning encompasses a sizable number of distinct approaches. Even though quite a few distinct approaches to marketing have already been used, there are nonetheless a great deal more that might be and really need to be applied. While methods based on reinforcement learning make it possible to simulate dynamically optimising behaviours in complicated settings, strategies based on unsupervised representation learning are particularly effective in gleaning knowledge from data sets that are themselves complex. The wide variety of PGM approaches has the potential to simulate complicated interactions between a large number of random variables and provide findings that are capable of being statistically analysed. Taking into consideration deep generative models and cutting-edge ensemble approaches are a couple of additional wonderful options to consider. In order to widen and improve the use of these technologies, we strongly encourage researchers to include not just these but also a variety of additional machine learning strategies into marketing research.

❖ **Extending the methods**

We also encourage academics, rather than just adopting existing applications for machine learning techniques, to develop their own original uses for these methods. Research in marketing and other areas of social science have a surprising amount of similarities in terms of the requirements that must be met. For example, it is widely believed to be capable of being understood in a great variety of different ways. Even though there have been efforts to simplify and make machine learning algorithms easy to understand, this is something that often occurs after the fact. The improvement of methodological practises would be substantially aided by advancements in this domain. It is necessary to have ex ante interpretability on the model's structure and the variable interactions. It is essential to have interpretability of the model structure and the variable interactions prior to running the model. The structure of the model as well as the interactions between the variables need to be able to be interpreted before it can be run. It is essential to keep this in mind while doing research that investigates connections, causal relationships, or makes advice. One other example would be any breakthrough that makes it feasible for procedures to manage dynamic customer decisions, as well as any innovation that makes it possible to draw statistical conclusions from data. These developments will be extremely useful to marketing in particular, but they will be advantageous to marketing and social science in general as well. Reinforcement learning, deep generative models, and probabilistic graphical models (PGM) are some of the approaches that are seen to offer the most potential for these breakthroughs. We would want to extend an invitation to the academic community to search for methodological advances at this fundamental level.

5. Analysis and Interpretation

The marketing industry has experienced a significant paradigm change as a direct result of the seamless integration of machine learning and artificial intelligence (AI), which combines the processing capacity of these technologies with the valuable human insights possessed by marketing professionals. This combination of processing power and insights has resulted in a huge shift in the marketing sector. As a consequence of this, the sector has gone through a substantial transformation. The results of our study uncovered a number of significant previously unknown facts. First, as a result of breakthroughs in artificial intelligence and machine learning, marketers are now able to make decisions based on data at rates that were previously unimaginable. This has opened up new opportunities for the industry. This is made feasible by the fact that correct insights can now be taken from large datasets. Consequently, this was previously impossible. As a direct consequence of this, predictive analytics are becoming more prevalent, which enables businesses to anticipate the behaviour of their customers and adjust their marketing strategies accordingly. A new era of hyper-personalization has begun as well, with AI-driven systems giving information that is particularly suited to each individual consumer. This was done in order to boost engagement and loyalty among customers. The era of hyper-personalization has officially arrived. The discussions, on the other hand, also place a focus on the moral repercussions of maintaining personal data, putting a significant emphasis on transparency and trust as the most essential attributes. The marketing process has been simplified thanks to automation that is driven by artificial intelligence, providing human marketers more time to focus on strategy and uniqueness. It is essential to find productive solutions to concerns about the privacy and security of data. Our research implies that the use of artificial intelligence (AI) in marketing will continue to expand, and it highlights the need of collaboration between data scientists and marketing professionals in order to make full advantage of AI. To summarise, using AI and machine learning in marketing calls for an approach that, in addition to being a step forward in terms of technology, is also a well-thought-out strategy that takes into account ethical considerations and the ingenuity of humans.

❖ **Fundamental Analysis Performance**

The labelling of the target values and the use of principle component analysis (PCA) are both included in the pre-processing of the data. There is no longer a significant connection between any of the features' measurements. This collection includes little under 6000 tweets in its entirety. After using the methods described above, the output of the model is then classified as having either a good or negative feeling. The effectiveness of machine learning algorithms may be evaluated based on the evaluation criteria that were discussed in the part that came before this one. The findings are compared in Table 3, which may be found down below (see below).

TABLE 3: MODELS FOR COMPARING PERFORMANCE IN BASIC ANALYSIS.

Metrics	LR	GNB	BNB	DT	RF	KNN	SVM	XGB	ANN
Precision	0.728	0.637	0.643	0.618	0.728	0.683	0.758	0.71	0.685
Recall	0.726	0.635	0.643	0.618	0.728	0.683	0.756	0.708	0.685
F1- score	0.725	0.633	0.643	0.618	0.728	0.683	0.756	0.708	0.685
Accuracy	0.726	0.635	0.643	0.618	0.728	0.683	0.756	0.708	0.685
AUC	0.72	0.62	0.63	0.64	0.74	0.68	0.76	0.73	0.68

This chart demonstrates that the task of anticipating public opinion in this investigation using ML algorithms does not give favourable results, as the table's title suggests. The “support vector machine” SVM approach is, by far, the most accurate of the available options, with a success rate of 76%. In addition to this, the efficiency with which these algorithms perform their functions. The area under the curve, also known as AUC, is shown for each method, and the ROC curves are compared with one another. The “support vector machine” SVM method has the greatest AUC rating out of all the available choices.

TABLE 4: PERFORMANCE METRICS FOR GNB AND LR MODELS

		Mean	**Median**	**Mode**	**Minimum**
GNB	0.708	0.63	0.64	0.64	0.63
	0.71	0.64	0.64	0.64	0.64
	0.73	0.62	0.62	0.62	0.62
LR	0.708	0.73	0.73	0.73	0.73
	0.71	0.73	0.73	0.73	0.73
	0.73	0.72	0.72	0.72	0.72

Table 4 compares the performance metrics of two alternative machine learning models: “Logistic Regression” (LR) and “Gaussian Naive Bayes” (GNB), respectively. The metrics are the mean, median, mode, and minimum, which, in turn, provide information about the central tendency, the value that occurs most often, and the lowest value that any model may attain. This comparison makes it possible to evaluate the relative performance of “Gaussian Naive Bayes” GNB and LR over a wide range of relevant statistical features, enabling this evaluation. To conduct a thorough study of these metrics, further background knowledge about the particular activity or dataset in issue would be required. “Long-term memory” (LSTM) neural networks and linear regression are two alternative methods for predictive modelling that are compared in Table 5. The R-squared (R2) statistic, the Explained Variation statistic, the “Mean Absolute Percentage Error” (MAPE) statistic, the Root Mean Square Error (RMSE) statistic, and the “Mean Absolute Error” (MAE) statistic are some of the metrics that might be utilised. It is standard procedure to utilise these factors when assessing the precision and propensity of regression models.

TABLE 5: PERFORMANCE COMPARISON OF LINEAR REGRESSION AND LSTM MODELS.

Metric	**Linear Regression**	**LSTM**
R2	1.0	0.99
Explained Variation	1.05	1.98
MAPE	1.75	2.92
RMSE	1.85	3.46
MAE	1.19	3.3

Table 5 reveals that Linear Regression earned a perfect R-squared value of 1.0, which indicates a perfect fit to the data, in contrast to the LSTM model, which performed well and received a score of 0.99 for its R2. This shows that linear regression is the most appropriate model to use. On the other hand, LSTM outperformed linear regression in terms of explained variation, “Mean Absolute Percentage Error” MAPE, RMSE, and MAE, all of which had greater values than linear regression did. These findings suggest that, despite the strong overall performance of both models, the LSTM model may produce a more accurate prediction in this specific situation when compared to Linear Regression. This conclusion is drawn from the fact that the LSTM model outperformed the Linear Regression model by a significant margin. This conclusion may be drawn as a result of the fact that the LSTM model performed better than Linear Regression. To determine which model is most suitable for a particular application, it may be necessary to do extra research and conduct an analysis of domain-specific features.

6. Result and Discussion

The use of artificial intelligence (AI) and machine learning has ushered in a new era of marketing that is marked by a shift in the paradigm. This relationship has made it possible for previously inconceivable computer capabilities and significant human discoveries to converge. Our research reveals how machine learning and artificial intelligence have made it feasible for marketers to improve their decision-making, tailor their interactions with customers, and improve their marketing strategies. These improvements have been made possible as a result of technological advancements. The discussions demonstrate that the technologies at issue are hastening a data-driven revolution and making real-time modifications and predictive models, both of which were previously unfeasible, possible. In this part, we will make an attempt to demonstrate how successful the strategy that was presented is in anticipating fluctuations in the stock market. Python is used to train the machine learning models that are used for this purpose. Python is also used to predict data that is unexpected. In this particular scenario, the market prognosis provided by the technical analysis is evaluated first, and only after that is the fundamental analysis taken into consideration. Figure 2 provides a condensed summary of the performance indicators for each of the three distinct classifiers. There are three main types of machine learning algorithms, and they are referred to as Decision Trees (DT), Random Forest (RF), and Bernoulli Naive Bayes (BNB). A number of different variables, including precision, recall, F1-score, accuracy, and area under the curve (AUC), are taken into consideration. The findings for Precision, Recall, F1-score, and Accuracy are the same for all three classifiers (DT, BNB, and RF), and the values for these metrics are comparable across all three classifiers. The accuracy rate is the most significant metric. For example, when this method is used to DT, BNB, and RF, the outcomes for Precision, Recall, and F1-score, respectively, are all 0.62, 0.64, and 0.73.

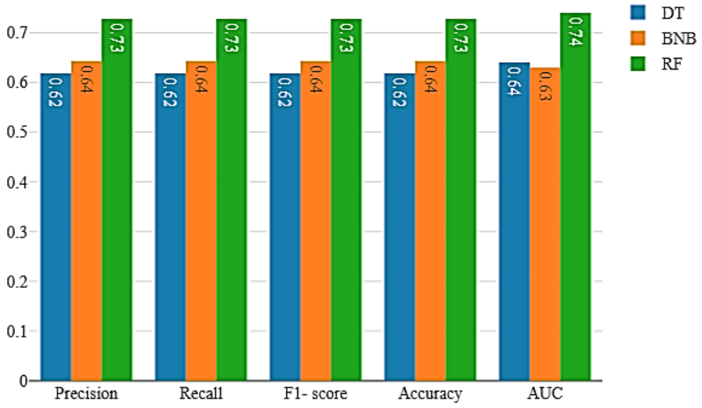

FIG 2: CLASSIFIER PERFORMANCE MEASURES: DECISION TREES, BERNOULLI NAIVE BAYES, AND RANDOM FORESTS

The Area Under the Curve (AUC) analysis, on the other hand, reveals that there is almost little volatility at all, with DT scoring 0.64, BNB scoring 0.63, and RF scoring 0.74. These measurements provide an all-encompassing perspective on the classification performance of each classifier. RF often has a greater area under the curve (AUC) than DT and BNB, despite the fact that all three classifiers have the same accuracy, recall, and F1-score. It is possible that further study and analysis will be required before deciding on a classifier to apply to a particular classification issue in order to choose the most appropriate method. The performance assessments of two distinct approaches to predictive modelling are compared and contrasted in Figure 3. These approaches are known as linear regression and long short-term memory (LSTM) neural networks, respectively. The method that makes use of linear regression can be shown on the left, while the strategy that makes use of LSTM neural networks can be seen on the right. R-squared (R2), Explained Variation, “Mean Absolute Percentage Error” (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are some of the metrics that are explored. Other measures include “Mean Absolute Error” (MAE) and “Mean Absolute Percentage Error” (MAPE). Additional measurements include the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), and the “Mean Absolute Percentage Error” (MAPE). A new form of statistic known as the “Mean Absolute Error” (MAE) may be calculated. There are two more measures known as the “Mean Absolute Error” (MAE) and the Root Mean Square Error (RMSE).

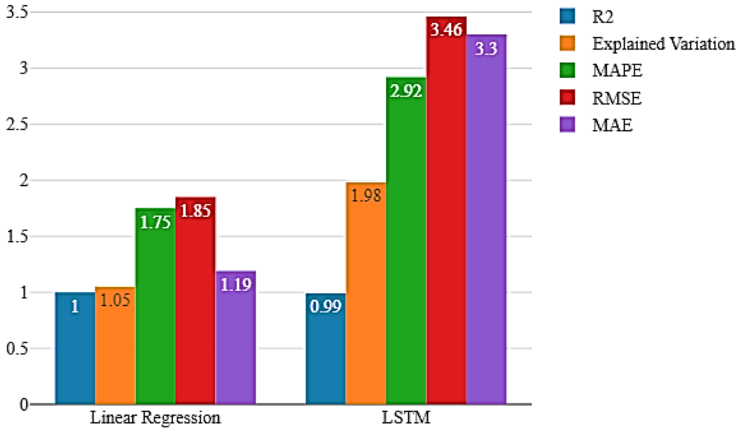

FIG 3: PERFORMANCE METRICS FOR LINEAR REGRESSION AND LSTM MODELS

Both the LSTM and the linear regression models provide metrics that are equivalent with regard to a wide variety of statistical variables (such as the mean, median, mode, and minimum). On the other hand, when using LSTM, a score of 0.99 for the R2 metric indicates that the model has strong predictive performance. When using linear regression, a model is considered to be an excellent representation of the data when it has an R2 value of 1.0. Both LSTM and linear regression are capable of explaining precisely 1.05 and 1.98 percent of the variance, respectively. In addition, the outcomes of RMSE, MAPE, and MAE are always the same, and LSTM performs superiorly than linear regression in terms of all of these error metrics. These measures make it possible to conduct an in-depth analysis of how good the models are in terms of their accuracy and their ability to anticipate. The use of linear regression, which provides a perfect fit in addition to lowered error metrics, may be of more benefit when used to this particular dataset or for this particular purpose. Nevertheless, it is very necessary to do an analysis of the circumstances and objectives that are specific to the selected business.

7. Conclusions

Autonomous artificial intelligence agents that are driven by methods of machine learning will thrive in every field of business and marketing over the next several decades due to the fast growth of technology, the massive quantities of data that are being created, and the severe competition. Academic research needs to make full use of the abundance of digital information that is currently available in order to address new significant issues in the field, deepen understanding of businesses and customers, and develop capacities for scalable and automated decision support that will be crucial for business managers. All of these things need to be accomplished in order to move the field forward. In order to make progress in this area, each of these tasks has to be completed. The use of information that has been digitally captured provides the possibility of accomplishing all of these goals. In light of all of these different considerations, it would seem that the use of methods that include machine learning has a great lot of potential for the solution of significant research issues. Because marketing research and machine learning focus on different aspects of the consumer experience, it may be challenging to integrate machine learning technology into marketing research in an efficient manner. Research studies on this topic often make use of a hybrid model, which is a kind of machine learning model that integrates the technical analysis and the fundamental analysis into a single framework. This model is called a hybrid. This is done in order to compensate for any deficiencies that may be present in the many separate algorithms. This might result in an increase in predictability and give an intriguing study topic for the years to come. According to the findings of this study, artificial intelligence is not yet capable of accurately predicting the movement of the stock market. The growth of artificial intelligence (AI), in particular when combined with advances in processing capacity, may make it possible, at some point in the not too distant future, to have access to models that produce more accurate stock market predictions. This may be made possible owing to the fact that AI has become more advanced. However, as of right now, there is not a trustworthy model that can exceed the performance of the stock market.

References

[1] Corbo, L., Costa, S., & Dabi, M. (2022). The evolving role of artifcial intelligence in marketing: A review and research agenda. *Journal of Business Research*, 128(March 2020), 187–203.

[2] Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artifcial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48, 24–42.

[3] de Cosmo, L. M., Piper, L., & Di Vittorio, A. (2021). The role of attitude toward chatbots and privacy concern on the relationship between attitude toward mobile advertising and behavioral intent to use chatbots. *Italian Journal of Marketing*, 1, 83–102.

[4] Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artifcial intelligence for decision making in the era of Big Data—Evolution, challenges and research agenda. *International Journal of Information Management*, 48(February), 63–71.

[5] Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research,* 69(2), 897–904.

[6] Huang, M. H., & Rust, R. T. (2021). A strategic framework for artifcial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30–50.

[7] Kurachi, Y., Narukawa, S., & Hara, H. (2018). AI chatbot to realize sophistication of consumer contact points. *Fujitsu Scientifc and Technical Journal,* 54(3), 2–8.

[8] Ma, L., & Sun, B. (2020). Machine learning and AI in marketing – Connecting computing power to human insights. *International Journal of Research in Marketing, 37(3)*, 481–504.

[9] Neha Sharma, P. William, Kushagra Kulshreshtha, Gunjan Sharma, Bhadrappa Haralayya, Yogesh Chauhan, Anurag Shrivastava, "Human Resource Management Model with ICT Architecture: Solution of Management & Understanding of Psychology of Human Resources and Corporate Social Responsibility", *JRTDD*, vol. 6, no. 9s(2), pp. 219–230, Aug. 2023.

[10] William, P., Shrivastava, A., Chauhan, P.S., Raja, M., Ojha, S.B., Kumar, K. (2023). Natural Language Processing Implementation for Sentiment Analysis on Tweets. In: Marriwala, N., Tripathi, C., Jain, S., Kumar, D. (eds) Mobile Radio Communications and 5G Networks. Lecture Notes in Networks and Systems, vol 588. Springer, Singapore. https://doi.org/10.1007/978-981-19-7982-8_26

[11] K. Maheswari, P. William, Gunjan Sharma, Firas Tayseer Mohammad Ayasrah, Ahmad Y. A. Bani Ahmad, Gowtham Ramkumar, Anurag Shrivastava, "Enterprise Human Resource Management Model by Artificial Intelligence to Get Befitted in Psychology of Consumers Towards Digital Technology", *JRTDD*, vol. 6, no. 10s(2), pp. 209–220, Sep. 2023.

[12] Anurag Shrivastava, S. J. Suji Prasad, Ajay Reddy Yeruva, P. Mani, Pooja Nagpal & Abhay Chaturvedi (2023): IoT Based RFID Attendance Monitoring System of Students using Arduino ESP8266 & Adafruit.io on Defined Area, Cybernetics and Systems.

[13] William, G. R. Lanke, D. Bordoloi, A. Shrivastava, A. P. Srivastavaa and S. V. Deshmukh, "Assessment of Human Activity Recognition based on Impact of Feature Extraction Prediction Accuracy," 2023 4th International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, 2023, pp. 1-6, doi: 10.1109/ICIEM59379.2023.10166247

[14] Mariani, M., & Fosso Wamba, S. (2020). Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. *Journal of Business Research,* 121, 338–352. Mayring, P. (2008). Qualitative Inhalts analyse (p. 6). Beltz Deutscher Studien Verlag.

[15] Nguyen, B., & Simkin, L. (2017). The Internet of Things (IoT) and marketing: The state of play, future trends and the implications for marketing. *Journal of Marketing Management,* 33(1–2), 1–6.

[16] Shrivastava, A., Chakkaravarthy, M., Shah, M.A., A new machine learning method for predicting systolic and diastolic blood pressure using clinical characteristics. In *Healthcare Analytics*, 2023, 4, 10021

[17] Shrivastava, A., Chakkaravarthy, M., Shah, M.A.,Health Monitoring based Cognitive IoT using Fast Machine Learning Technique. In *International Journal of Intelligent Systems and Applications in Engineering*, 2023, 11(6s), pp. 720–72

[18] Shrivastava, A., Rajput, N., Rajesh, P., Swarnalatha, S.R., IoT-Based Label Distribution Learning Mechanism for Autism Spectrum Disorder for Healthcare Application. In *Practical Artificial Intelligence for Internet of Medical Things: Emerging Trends, Issues, and Challenges*, 2023, pp. 305–321