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A Study of Impact and Applications of Predictive Analytics in Sales Forecasting

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Abstract: Predictive analysis has become an efficient tool and procedures now a day for many industries, organization, firms and service sectors.
In sales, predictive analytics refers to the software and/or procedures that evaluate past and present sales data in order to forecast sales results and enhance efficiency. A vast amount of first-party and third-party customer/prospect data is available these days to sellers and marketers.
Indeed, sellers and marketers frequently feel overpowered by the sheer amount of data when deciding how to leverage it to get desired outcomes.
That issue is resolved by predictive analytics in sales, which uses artificial intelligence systems to assist sales representatives in understanding customer and sales pipeline information.
Advances in data analytics are being used by an ever-increasing number of organizations to identify patterns and trends, increase productivity, and make more informed business decisions. In this paper, we will discuss and analyze the role and impact of the predictive analytics in sales.
Keywords: Predictive Analytics, Predictive Modeling, Sales Forecasting, Data Mining, Regression, Customer.

I. INTRODUCTION

The phrase "predictive analytics" refers to a broad range of statistical and analytical methods that are used to create models that forecast future behavior or events. Depending on the behavior or event that these predictive models are forecasting, these models take on different forms.
The term "predictive analytics" is derived from the phrases "predict" and "analysis," although it operates backwards, analyzing data before making predictions.
Humans are naturally curious about and inclined to forecast the future. The majority of predictive models produce a score; a greater score denotes a higher chance that the specified behavior or event will occur. .Predictive analytics uses advanced techniques like machine learning to forecast future events based on past data that has already been observed. Many methods, such as filtering and data correlation, are used to gather and process the historical data.
AI and machine learning are used by predictive sales analytics software to gather information about prospects and customers and track their behavior throughout the sales process. These insights are then applied to sales projections and pipeline performance by the predictive analytics programme.
A type of technology called as predictive analytics is used to forecast future unknowns. To get at these conclusions, it uses a number of methods, such as modelling, statistics, data mining, artificial intelligence (AI), and machine learning. For example, data mining is the process of analyzing big data sets to find patterns in them. Except for big blocks of text, text analysis functions in the same way.

There are four steps in the prediction process:
1) Gather and preprocess the raw data;
2) Convert the preprocessed data into a format that the (chosen) machine learning technique can handle with ease;
3) Utilize the altered data to generate the learning model (training);
4) Use the previously constructed learning model to report predictions to the user.

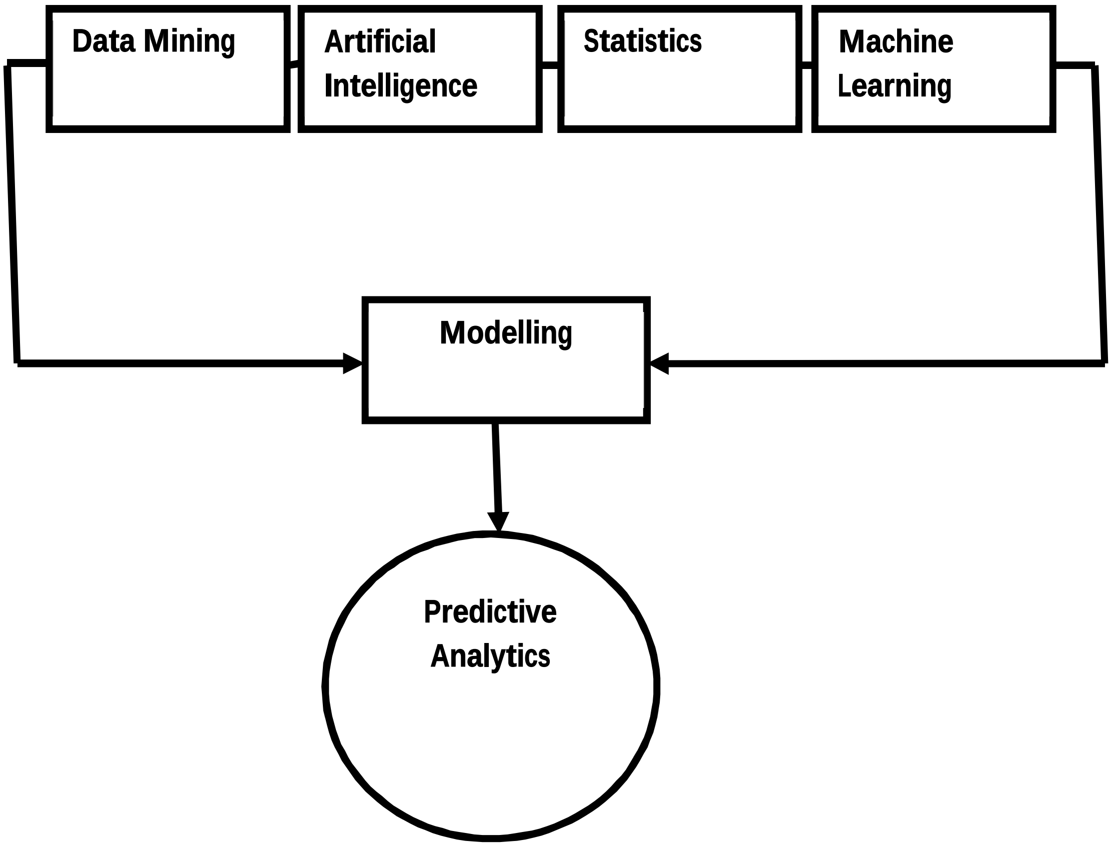

Fig. 1: Predictive Analytics Constituents

II. DATA MINING AND PREDICTIVE SALES ANALYTICS

Predictive analytics is the way of the future for data mining **[1].** There is a big distinction between data extraction and data mining, despite the fact that the terms are sometimes used interchangeably. The process of extracting data from one source and entering it into a desired database is known as data extraction. As a result, data can be "extracted" and added to a conventional database or data warehouse from a source or legacy system. The extraction of subtle or concealed prognostic information from sizable databases or data warehouses is known as data mining, on the other hand. Likewise referred to as knowledge discovery. The process of looking for patterns in data repositories is known as data mining. Data mining employs computational methods from pattern recognition and statistics to achieve this goal. Thus, the definition of data mining is the process of searching for patterns in data.

The methods and tools used in data mining create a predictive analytical model. Accessing large databases in order to retrieve data is the initial stage. In order to uncover hidden patterns and predictive data, sophisticated algorithms are used to process the resulting data. Although there is a clear link between statistics and data mining, data mining techniques have their roots in non-statistics domains. A number of applied knowledge streams, including database administration, data visualization, machine learning, artificial intelligence, and pattern recognition, converge at data mining. The majority of data mining techniques includes the nearest neighbour approach, artificial neural networks, decision trees, genetic algorithms, and rule induction. Using predictive analytics, one can ascertain the possibility of a condition occurring or the likely future course of an occurrence. This area of data mining is focused on forecasting future trends and probability. Predictive analytics, which encompasses clustering, decision trees, market basket analysis, regression modeling, neural nets, genetic algorithms, text mining, hypothesis testing, and more, is used to automatically analyze vast volumes of data containing various factors **[2]**.

The "predictor," a variable that may be assessed to help an individual or institution forecast its future behaviour, is the fundamental component of predictive analytics. When determining the risk factor for granting a credit card to an applicant, a credit card firm might, for instance, take into account the applicant's age, income, and credit history. A predictive model, which is used to estimate future probabilities with a sufficient degree of confidence, can be created by combining multiple predictors.

Predictive modeling involves gathering data, creating a statistical model, making predictions, and validating (or updating) the model as new data become available **[2].** Combining statistical analytical methods with business knowledge, predictive analytics generates insights from company data. These perceptions aid companies in comprehending the behavior of consumers, vendors, distributors, buyers, and so forth **[2]**.

A. Principal Objectives of Using Data Mining in Predictive Model

Developing a model that may be used to forecast the occurrence of an event is the main goal of data mining. The process of building a model involves extracting knowledge from historical data and presenting it in a way that makes the final product applicable to new scenarios. Analyzing data sets yields valuable information that can be used to use one or more data mining techniques to detect trends in the data that can be used to forecast future trends or behaviors, or to locate patterns in the data that were previously unknown.

There are two primary types of data mining: unsupervised and supervised

In supervised learning, a model is created from training data to identify patterns in the data that, when combined with a set of parameters, can be used to predict a label or value.

The process of developing predictive models utilizing a set of past data containing the outcomes we are attempting to forecast is known as supervised learning. Which algorithm is used for this—a classification or regression—depends on the kind of data.

B. Methods Used

The statistical technique known as regression was created by mathematician and Charles Darwin's cousin Sir Frances Galton (1822–1911). The relationship between one or more independent or predictor variables and a dependent or response variable (which has continuous values) can be modelled using regression analysis **[3]**. The most basic type of regression, known as linear regression, predicts the value of y determined by the input variable, x, by using the straight line formula ($y = mx + c$) to get the proper values for m and c.

More sophisticated methods, like multiple regression, enable the fitting of more complex models, such higher order polynomial equations, and the use of multiple input variables **[3]**. One reputable and well-established statistical method is regression.

In order to anticipate the class label of unlabeled data, classification is the set of data mining techniques used to fit discrete (categorical) data to a known structure. Classification algorithms are usually implemented in three stages. The training and testing stages employ labelled data, which is data that contains predetermined class labels. To fit a classifying model to the data, training uses a subset of the data. Subsequently, the models are used in the testing phase to attempt to predict the class labels. The accuracy of the model is assessed by validating the predictions using the actual values. This provides input on how well the models function and whether or not additional models need to be developed. When a workable model has been developed and successfully tested, the classifier is applied to unlabeled data. We refer to this as the deployment phase. Bayesian classification, decision trees, neural networks with back-propagation, genetic and evolutionary learners, and neural networks are examples of common classification techniques.

The challenge of attempting to uncover hidden organization in unlabeled data is known as unsupervised learning. Unsupervised algorithms operate without supervision because, in contrast to supervised algorithms, they do not learn from past data with known labels. Clustering, characterization, association rule mining, and change and deviation detecting algorithms are examples of common unsupervised procedures.

Predictive analytics is the application of a range of statistical methods, including modelling, machine learning, data mining, and game theory, to analyze historical and present data in order to forecast future occurrences **[4].** Utilizing patterns discovered in transactional and historical data, predictive algorithms pinpoint possibilities and hazards. Models are used to assess risk or potential related to a certain set of situations by capturing relationships among numerous components.

Predictive analytics forecasts future occurrences using data-mining techniques and generates recommendations based on these forecasts. Predictive analytics' primary method is to identify correlations between explanatory variables and predicted variables based on historical data, then use those links to forecast future events **[5]**.

It is crucial to remember, nevertheless, that the degree of data analysis and the caliber of the assumptions will have a significant impact on the results' correctness and usefulness. Predictive modelling, "scoring" data with predictive models, and forecasting are commonly referred to as predictive analytics. Nonetheless, the phrase is being used more frequently to refer to related analytical fields including descriptive modelling, decision modelling, and optimization.

Both of these fields need thorough data analysis and are frequently employed in business for segmentation and decision-making, while their goals and the statistical methods that support them differ. Predictive models evaluate by analyzing historical performance, but Relationships in data are quantified by descriptive models **[6]**.

To be able to forecast the outcomes of decisions containing numerous factors, decision models define the link between all the components of a decision, including the decision, the forecast results of the decision, and the known data (including outcomes of predictive models) **[1].** These models can be applied to optimization to maximize some results and minimize others.

III. TECHNIQUES OF PREDICTIVE-ANALYTICS

Predictive models use historical and transactional data to find trends that indicate various dangers and opportunities. The decision-making process for future transactions is guided by forecasting models, which record correlations between numerous aspects to enable assessment of the risks or opportunities associated with a specific set of conditions **[7] [8]**.

There are some basic techniques used in Predictive Analytics: These are:

1) *Decision Tree:* Given its ease of understanding and ability to manage missing variables, this is one of the greatest predictive analytics tools available. Using branching, the decision trees illustrate the potential outcomes or choices associated with each choice. Every leaf represents a categorization, such as yes or no, while every branch represents a potential choice between two or more possibilities.
2) *Regression:* For various settings, there are three different regression techniques. Regression analysis can be applied differently to different data queries, but in general, predictive analytics regression helps to determine the correlations between variables. If a result can be attributed to only one independent variable, then linear regression is employed. When there are several independent factors that affect an outcome, multiple regression is performed. Additionally, when the dependent variable is binary, logistic regression is applied.
3) *Neural Network:* The most intricate predictive analytics method is this one. It makes use of algorithms to identify potential connections between data sets. Artificial Intelligence is used by neural networks, which enables more complex pattern identification.
4) *Data-Profiling and Transformation:* Functions that alter row and column attributes and analyze dependencies, data formats, merge fields, aggregate records, and create rows and columns are known as data profiling and transformations.
5) *Sequential Pattern Analysis:* Sequential pattern analysis shows the connections between the data rows. Finding frequently observed sequential occurrences of objects throughout time across ordered transactions is the goal of sequential pattern analysis.
6) *Time Series Tracking:* An ordered succession of values at varied time intervals at the same distance is known as time series tracking. Time series analysis provides information on data points collected over a period of time.

   Advanced predictive analytics methods include time series forecasting, association analysis, and classification-regression, to mention a few. Classification predicts the value of a numeric variable of interest or assigns an object to a preset class based on attributes in the data. A statistical tool for examining relationships between variables is regression analysis.

An association analysis explains important correlations between different data points. Time series analysis is used to predict a measure's future value based on its historical values.

IV. PREDICTIVE MODELS

While most experts concur that predictive analytics demands a high level of skill, some even suggesting that there is an artistic and highly creative aspect to model creation, predictive models typically require a few fundamental stages to be developed. The steps can be briefly described below:

1) *Project-Definition:* Establish the project's business goals and intended results, then convert them into tasks and objectives for predictive analytics.
2) *Exploration:* Determine the best relevant data and model development strategy by analyzing the source data.
3) *Data Preparation:* Choose, extract, and modify the data to be used as a basis for models.
4) *Model Building:* Develop, test, and validate our models, then assess if they will achieve the project's objectives and metrics.
5) *Deployment:* Utilize model outputs to inform business decisions and procedures.
6) *Model Management:* Handle models to enhance performance (accuracy), regulate access, encourage reusing, standardize toolkits, and reduce superfluous tasks.

The majority of specialists believe that the most time-consuming step in developing predictive models is the data preparation stage.

V. PROCESS CYCLE OF PREDICTIVE ANALYTICS

For predictive analytics, we follow a process cycle as shown in Fig. 2 below.

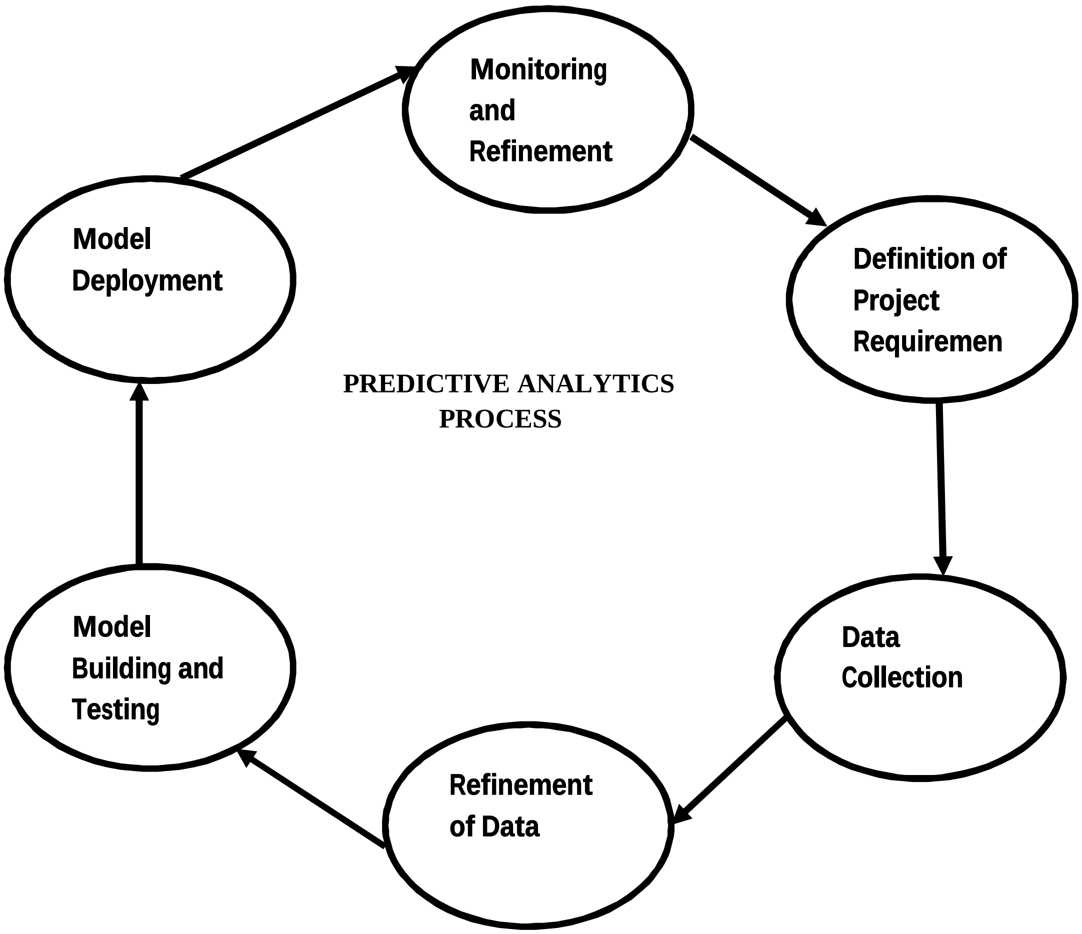

Fig. 2: Predictive Analytics Process Cycle

The steps of process cycle are summarized below:

1) *Definition of Project Requirements:* This Specify the goals of the project, its objectives, its scope, and the data sets that will be used. The needs of the parties involved may not always be well stated. It then becomes our duty to ascertain with precision what is to be anticipated and whether the result resolves the stated issue. Depending on how the problem is defined, the dynamics of the solution and the result are entirely different. Predictive analysis's most crucial step is turning a business problem into an analytical one. Therefore, specify what is expected and how the result will seem in precise terms.
2) *Data Collection:* The process of collecting data entails obtaining the information needed for analysis. It involves the history or previous data that will be the subject of a predictive study, obtained from an authorized source. Get all the information we require in one location. Incorporate a range of recent and historical data sets from many sources.
3) *Refinement of Data:* Refining our data sets is a process we call data cleaning. During the data cleansing process, redundant and inaccurate data are eliminated. It entails purging our data sets of superfluous and duplicate information. To prepare our data for analysis, clean, prepare, and combine it. To raise the caliber of our predictive data set, eliminate outliers and find any missing data.
4) *Model Building and Testing:* Using a variety of algorithms, we create prediction models based on the patterns we see in this step of predictive analysis. It calls for familiarity with MATLAB, R, Statistics, Python, and other languages. We also use standard statistic models to test our hypothesis. In predictive analysis, it's a critical phase. In this step, we run a number of tests to see how effective our model is. Here, we offer sample input sets to verify our model's validity. At this point, the model's accuracy has to be assessed.

5) *Model Deployment:* When we deploy our model, we make it function in a real-world setting, facilitating regular conversation and making it usable. Install and run predictive model on fresh data. Obtain reports and results.
6) *Monitoring and Refinement:* Keep an eye on our models on a regular basis to assess performance and make sure the results are correct. It involves comparing the performance of model predictions to real data sets. We continuously assess our model's performance to make sure it's producing the desired outcomes. As necessary, adjust and optimize our model.

VI. RELATED WORK

As analysts look for areas of space and time with unusually high incidences of events (hotspots), R. Maciejewski et al. **[9]** proposed a model for spatiotemporal data and developed a predictive visual analytics toolkit that gives analysts linked spatiotemporal and statistical analytic views. Using a combination of kernel density estimation for event distribution and seasonal trend decomposition via loss smoothing for temporal predictions, the system predicts spatiotemporal occurrences. Yue, J., and others **[10]** They highlighted RESIN, an AI blackboard-based agent that uses interactive visualization and mixed-initiative problem solving to enable analysts to explore and pre-process vast amounts of data in order to perform predictive analytics. In this paper, they specifically address predictive tasks that are concerned with predicting future trends.

In order to facilitate the creation of games inside a predictive analytics framework, R. M. Riensche et al. **[11]** presented a methodology and architecture that is intended to collect input data, compute the outcomes of intricate predictive technical and social models, and present the findings in an interesting way. Predictive analytics approaches were used by Z. Huang et al. **[12]** to create a decision support system for complicated network operation management. This system assisted operators in anticipating possible network failures and modifying the network in response to unfavorable circumstances. The resulting decision support system makes it possible to continuously monitor network performance and converts vast amounts of data into knowledge that can be put to use.

Sanfilippo et al. **[13]** proposed new techniques for anticipatory critical thinking assist naturalistic decision making by utilizing a multi-perspective approach to predictive modeling. In this study by R. Banjade et al. **[14]**, the linear regression technique is examined for the analysis of large-scale datasets with the goal of providing e-commerce customers with helpful recommendations through offline computations of model results. For both numerical and categorical data, V. H. Bhat et al. **[15]** offer a novel pre-processing step with missing value imputation. In their work, they have adopted a hybrid approach that combines Classification and Regression Trees (CART), Genetic Algorithms to impute missing continuous values, and Self Organizing Feature Maps (SOFM) to impute categorical values.

As a preliminary step, V. H. Bhat et al. **[16]** presented an effective imputation technique that combines a hybrid CART and genetic algorithm. The pre-processed dataset is utilised as the basis for prediction using the traditional neural network model. N. Chinchor et al.'s tutorial **[17]** covers the integration of visual analytics and multimedia analysis to handle data from many sources, with various aims or purposes, and comprising various media kinds and combinations of types. The mixture that emerges is known as multimedia analytics. A three-way comparison of prediction accuracy between CART models, NNs, and nonlinear regression was carried out by M. A. Razi et al. **[18]** utilizing a continuous dependent variable along with a set of dichotomous and categorical predictor variables.

VII. APPLICATIONS OF PREDICTIVE ANALYTICS IN SALES AND FORECASTING

Now a days, predictive analysis is being used in many sectors, such as Sales and Sales forecasting, marketing, retail, health care, finance, cyber security and many more. However, this paper deals with only sales related applications of predictive analytics. Some of the most conspicuous applications of predictive analytics in sales are:

A. Sales Forecasting

Predicting future sales using historical data is one of the most obvious uses of predictive sales analytics. Unlike setting lofty goals, historical data provides us with a realistic and accurate picture of how much revenue our team should be generating within a given time frame. We can predict future revenue with a high degree of accuracy by comparing our current transactional and customer interaction data (emails, meetings, phone calls, etc.) to actual sales outcomes. This knowledge can be used to allocate resources and manage our workforce more effectively. Moreover, reducing waste makes our business more flexible so we can react quickly to changing market conditions.

We can also assess whether we are on track by comparing our company's performance to industry averages using historical sales data. We may now start the process of figuring out the main reason why our sales numbers aren't matching industry averages and making the required adjustments.

Predictive analysis should be used by businesses primarily to improve forecasting accuracy. In order to estimate the future sales rate, a proper sales forecast takes into account rivals, historical sales, industry trends, and other factors. Key metrics in the process are likely to be missed if technology is not applied. As a result, manually processed insights frequently contain mistakes.
This danger is reduced by using machine learning techniques. Every set of data is precisely measured by predictive analysis, which also yields useful insights. We may use this to help sales staff to set smart goals, which stand for specific, measurable, achievable, relevant, and time-bound.

B. Customer Perceptive

Consumer purchasing habits are subject to alter at any time and for any reason. Oour sales rate will inevitably decline if you don't continuously monitor their purchasing patterns. With the use of predictive analytics, you may better understand your customers' demands by looking at their data. It helps you adjust your sales strategy by mapping the changes in their requirements.
Using data-driven actionable insights, We can identify what appeals to our target clients and train our sales force to make tailored pitches. It improves our ability to manage client demands and give them the best possible experience. Our sales team will perform better if they have sufficient insight into our consumers' needs. Sales professionals will be skilled at solving clients' issues and maintaining customer satisfaction.

C. Sales Innovation

We need to be able to quickly adjust to shifting trends, client expectations, and marketing conditions if we want to stay competitive. A well-thought-out predictive sales analytics programme might easily become our competitive advantage in such a fast-paced, dynamic business climate.
We can forecast changes in the market with accuracy when you have access to reliable data. With this kind of vision, we may disrupt our own company, use cutting-edge technology to develop fresh, creative business concepts, and better serve our clients' demands before a more astute, data-driven rival does.
Future winners in every industry will be those that can use data to swiftly detect changes in the market and be the first to react with solutions that best satisfy customers' expectations.

D. Process Optimization

We can make sure that you are constantly saying the right thing to the right customer at the right time by adopting a data-driven approach. Predictive sales analytics can be used to streamline your sales process, shorten the sales cycle, and significantly boost revenue and profits.

E. Sales Campaign

Managing successful marketing campaigns is essential to increasing sales. We may get KPIs related to campaign exposure, engagement, and conversion rates with predictive analytics. It also enables you to compare your performance to that of your rivals and take success and failure from them. This assists you in creating a campaign that generates quality leads and appeals to your target market.

F. Customer Retention

Frederick Reichheld of Bain & Company conducted research that demonstrates that a 5% improvement in client retention rates results in a stunning 25% to 95% increase in earnings. To ensure the maximum satisfaction with clients and retention rates possible, our sales force should be aware of who their major clients are and concentrate on taking care of them. Though transactional data might assist us in identifying additional accounts that are expanding rapidly, we most likely already know who are our major accounts. Large accounts are something you just cannot afford to lose, so we must be able to recognize them and give our staff high attention. Esteban Kolsky's research indicates that while 67% of consumers cite negative experiences as the cause of their turnover, only 1 out of 26 dissatisfied customers files a complaint.
We may identify at-risk accounts and proactively reach out to consumers to resolve their problems and ensure complete satisfaction by using predictive sales analytics to uncover the top reasons that lead to client turnover. This includes figuring out which clients have enrolled in our product's trial but have not started using it yet. If we are able to locate these accounts during the trial period, we may get in touch with them and provide support or lessons to help them through the on-boarding process and realize the complete benefits of utilizing our product.

G. Asset Optimization

A thorough understanding of both human and artificial asset utilisation is provided by predictive analytics. It helps you find business process bottlenecks by concentrating attention on areas that require enhancements. Making the best use of your assets will drastically save operating expenses, which will boost earnings.

H. Risk Management

Every business faces dangers. Global wars, shifting economic conditions, growing fuel costs, etc., can have a positive or negative effect on corporate outcomes. When producing insights, predictive analytics considers several situational and dangerous aspects. This aids in the identification of risks and their mitigation prior to a significant impact on your company. Early problem solving helps you maintain a high sales rate and stay competitive in the market.

VIII. CONCLUSION

Although sales forecasting is not a new concept, technology has greatly improved its accuracy and efficacy. The future is never entirely predictable. However, making data-driven judgements is aided by using a proper predictive sales evaluation approach. The limitations of human reasoning and bias are replaced by objective models based on algorithms that forecast in predictive analytics. This increases the likelihood of success and boosts sales. It assists us in comprehending the demands of our clients and prods you to concentrate your efforts in the most important areas. You establish attainable objectives and use systematic and long-term tactics to assist your sales staff in reaching them. With hundreds of options for every product these days, predictive sales analysis is our best chance to lead your sector.

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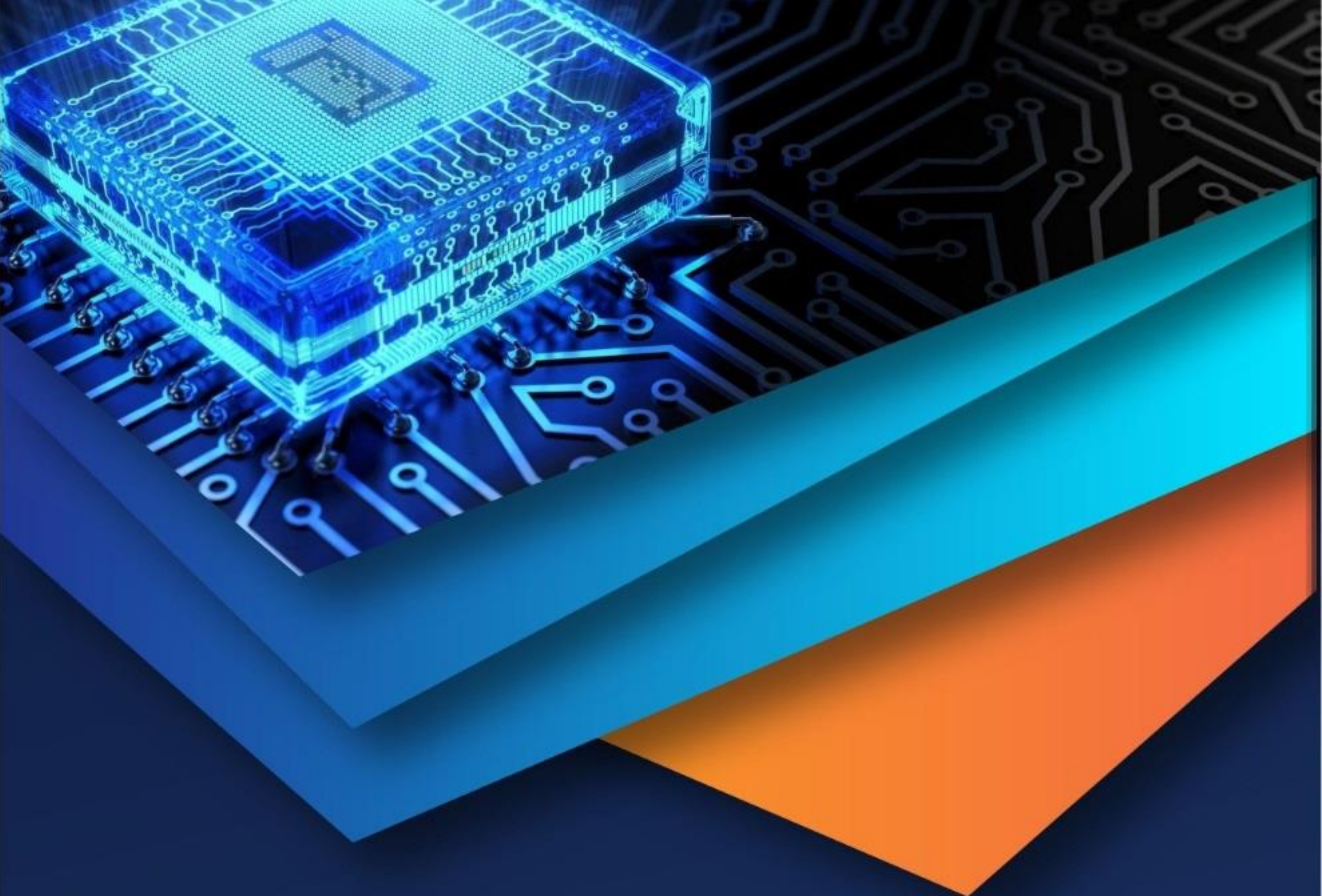

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