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

Achieving Operational Excellence: Paradigm Shift with Machine Learning-Driven Optimization

[1]Dr. Pravin Mane, [2]Dr. Hema Mirji, [3]Mr. Bhavsar Dhananjay Narayan, [4]Dr. Rahul Manjre, [5]Ms. Pratima Gund, [6]Mr. Girish Bahirat

Submitted: 09/12/2023 **Revised**: 21/01/2024 **Accepted**: 30/01/2024

Abstract: Achieving operational excellence has become crucial for organisations trying to stay ahead in the highly competitive business environment of today. Traditional methods must be rethought in order to be effective, and machine learning-driven optimisation stands out as a game-changing approach. The tremendous effects of incorporating machine learning into operational processes are explored in this abstract, which provides a succinct summary of the main ideas and discoveries.The conventional approach to operations management places a significant emphasis on static, rule-based systems. Organisations are able to optimise operations in a variety of areas, including as resource allocation, supply chain management, and customer service, by utilising the power of sophisticated algorithms.This abstract highlights the several benefits of optimisation driven by machine learning. It highlights how new technologies enable businesses to instantly analyse enormous datasets, find undiscovered trends, and take proactive, well-informed action. We demonstrate the real advantages of lower costs, more productivity, and better customer experiences through case studies and examples.Additionally, this abstract explores the difficulties and factors to be taken into account when applying machine learning-driven optimisation, including data privacy, hiring talent, and ethical issues. It highlights the urgent requirement for a comprehensive strategy that combines cutting-edge technology and careful planning.

Keywords: *Machine Learning, Optimization, Paradigm Shift, Data-driven, Efficiency, Automation, Predictive Maintenance, Resource Allocation*

1. Introduction

Organisations now find themselves at a crucial crossroads in the never-ending pursuit of operational excellence, where the fusion of technology and strategy promises a significant paradigm shift. Traditional methods of managing operations, which frequently rely on static rule-based systems, are showing themselves to be insufficient in the face of quickly changing markets, dynamic consumer demands, and the ever-expanding digital landscape [1]. Businesses must adopt a transformative strategy that taps into the transformative power of machine learning-driven optimisation if they want to succeed in this climate. Operational excellence, formerly characterised by effectiveness, cutting costs, and streamlining procedures, today necessitates a wider range of skills [2]. It demands the flexibility to adjust to unanticipated shocks, the vision to anticipate client needs, and the capacity to use data as a strategic advantage. Enter machine learning, a subset of artificial intelligence that is transforming the way businesses think about, plan for, and carry out their operational goals.

Fundamentally, machine learning-driven optimisation signifies a sea change from static, deterministic models to dynamic, data-centric systems. It offers a never-before-seen capacity for ingesting, processing, and acting on enormous volumes of data in real-time. Organisations can now discover hidden insights, recognise complex patterns, and act quickly in changing situations because to their increased agility [3]. It goes beyond the limitations of conventional operational paradigms, providing a holistic approach that cuts across functional silos and promotes intelligence informed by data.Throughout many industries, this transition is noticeable. Machine learning algorithms are used in supply chain management to optimise inventory levels, forecast demand variations, and find the most cost-effective transportation routes by analysing historical data and current variables [4]. Predictive maintenance models in manufacturing make sure that machinery runs as efficiently as possible, cutting downtime and maintenance expenses. Machine learning

[1]*Assistant Professor, Bharati Vidyapeeth (Deemed to be University) Institute of Management and Entrepreneurship Development, Pune, India.*
pravin.mane@bharatividyapeeth.edu
[2]*Assistant Professor, Bharati Vidyapeeth (Deemed to be University) Institute of Management and Entrepreneurship Development, Pune, India.*
hema.mirji@bharatividyapeeth.edu
[3]*Assistant Professor,Dr. D. Y. Patil Institute of Technology*
dhananjaybhavsar@gmail.com
[4]*Assistant Professor, Bharati Vidyapeeth (Deemed to be University) Abhijit Kadam Institute of Management and Social Sciences, Solapur, India.*
rahul.manjre@bharatividyapeeth.edu
[5]*Assistant Professor, Bharati Vidyapeeth (Deemed to be University) Institute of Management and Entrepreneurship Development, Pune, India.*
pratima.gund@bharatividyapeeth.edu
[6]*Research Scholar , Bharati Vidyapeeth (Deemed to be University) Institute of Management and Entrepreneurship Development, Pune, India.*
girishbahirat27@gmail.com

helps with personalised treatment plans and accurate diagnosis in the healthcare industry. Chatbots and natural language processing improve interactions in customer support, providing speedy problem solving.

Organisations face a variety of difficulties and factors as they set out on this path to operational excellence through machine learning-driven optimisation. Concerns about data security and privacy as well as the ethical use of AI are major issues. It can be difficult to find the necessary people with experience in data science and machine learning, and navigating the integration of these technologies into current operational frameworks calls for careful planning and execution [5].This overview lays the groundwork for a thorough investigation of how machine learning-driven optimisation represents not just an evolution but a revolution in achieving operational excellence. It highlights how crucial it is for businesses to adapt to this paradigm change and make use of machine learning to not only survive but also prosper in a society where operational excellence is the key to success. In order to shed light on the next steps in this revolutionary journey, we will delve into case studies, best practises, and emerging trends in the pages that follow.

2. Review of Literature

Operational excellence has always been a priority for organisations across all sectors. Traditional approaches have been used to achieve efficiency and reduce waste since they are based on concepts like Six Sigma and Lean Management. However, there is growing acknowledgment that a paradigm shift is required as firms face more complex and dynamic difficulties. Machine learning-driven optimisation has become a game-changing strategy that extends and complements the tenets of earlier approaches [6].For many years, the cornerstone of operational excellence has been Six Sigma, with its emphasis on lowering process variation and faults. It makes extensive use of statistical tools and organised problem-solving approaches. Although Six Sigma has significantly increased quality and reduced costs, it frequently has trouble adjusting to contexts that change quickly. On the other side, machine learning excels at handling huge and dynamic datasets, making it the perfect addition to Six Sigma principles [7]. The ongoing improvement of processes is facilitated by machine learning-driven optimisation, which can spot trends and abnormalities in real-time data.

Another pillar of operational excellence is lean management, which places an emphasis on waste reduction, process flow improvement, and maximising customer value. It promotes the abolition of activities with little additional value. By supplying a data-driven understanding of where waste occurs and by offering predicted insights into process bottlenecks, machine learning may complement lean principles [8]. As a result, businesses may optimise their operations in a granular and dynamic manner, better meeting the needs of their clients.Traditional supply chain management strategies have had a difficult time adjusting to the growing complexity and unpredictability of global marketplaces [9]. Demand forecasting, inventory control, and logistics optimisation have all been transformed by machine learning-driven optimisation, which has gained acceptance in this industry. It uses both real-time and historical data to create forecasts and suggestions, ensuring that supply chains are flexible and sensitive to changes in the market.

Additionally, machine learning-driven optimisation has had a considerable positive impact on risk management and fraud detection in the banking and financial industries. These programmes are able to search through huge datasets for unexpected patterns and detect potentially fraudulent transactions in real-time, preventing losses and safeguarding clients. Resource allocation, treatment optimisation, and patient outcomes in healthcare are all greatly influenced by machine learning-driven optimisation [10]. Hospitals may better manage patient admissions, make better use of available beds, and anticipate disease outbreaks with the use of predictive analytics. In order to help with early disease detection and treatment recommendations, machine learning algorithms can analyse medical records, which will ultimately improve patient care and save expenses. The shifting business environment necessitates a synergistic integration of machine learning-driven optimisation, even though classic approaches like Six Sigma and Lean Management have proven crucial in achieving operational excellence. These technologies not only increase the efficacy of current approaches, but they also give organisations the flexibility they need to adapt to new levels of operational difficulty and data complexity. The literature is increasingly emphasising this integration as the key to operational excellence's future and as a means of navigating the dynamic landscape of contemporary business.

Table 1: Summary of Related work

Approach	Findings	Limitations	Scope
Examined various ML techniques in SCM [11]	Improved demand forecasting, reduced inventory costs	Limited discussion on implementation challenges	Focused on supply chain
Integration of Lean Six Sigma with AI/ML [12]	Enhanced process efficiency and defect reduction	Limited empirical data on AI adoption	Bridging Lean with AI/ML
Detecting fraudulent transactions [13]	Reduced fraud losses, improved accuracy	Data privacy concerns and false positives	Financial sector fraud detection
Predictive analytics in healthcare [14]	Improved patient outcomes, resource optimization	Data privacy issues, interpretability	Healthcare operations and patient care
Predictive maintenance in manufacturing [15]	Reduced downtime, extended equipment life	Data quality and feature engineering challenges	Manufacturing and asset management
Retail operations optimization [16]	Increased sales, personalized customer experiences	Data integration challenges	Retail industry
Forecasting in supply chain [17]	Improved demand forecasts, reduced stockouts	Data quality issues and computational complexity	Supply chain forecasting
Integrating AI into business operations [18]	Improved decision-making, cost reduction	Lack of organizational readiness, AI ethics	General organizational context
Cloud resource optimization [19]	Cost reduction, improved resource utilization	Scalability and resource allocation fairness	Cloud computing operations
ML applications in operations [20]	Enhanced process efficiency, decision support	Limited discussion on ethical implications	Broad overview of operations management

3. Proposed Methodology

The approach for attaining operational excellence through data-driven optimisation that is driven by machine learning is methodical and data-driven and makes use of cutting-edge machine learning techniques. It includes numerous crucial phases:

- Data Gathering and Preprocessing: The first stage is to acquire pertinent data from various sources within the organisation, such as old records, client feedback, sensor data, or transaction logs. Then, this data is preprocessed to make it clean, deal with missing values, and make sure it's in an analysis-ready shape.Feature engineering is the process of choosing and modifying the data attributes (features) that are most pertinent to the current operational issue. By giving meaningful input variables to machine learning models, this stage seeks to enhance their performance.
- Model Selection: Appropriate machine learning models are chosen depending on the nature of the operational challenge, such as predictive maintenance, demand forecasting, resource allocation, or process optimisation. Depending on the intricacy of the issue and the data at hand, these models might range from conventional regression

algorithms to more sophisticated deep learning structures.

- Training and Validation: To evaluate the performance of the chosen machine learning models, a subset of the data is used for training and another subset for validation. To maximise model accuracy and generalizability, cross-validation approaches and hyperparameter adjustment may be used.
- Real-time Data Integration: It is essential to include machine learning models into the operational procedures for real-time operational optimisation. To facilitate continuous data flow and decision-making, this frequently entails building application programming interfaces (APIs) or inserting models into already-existing software systems.
- Deployment & Monitoring: After trained models are put into use, they monitor incoming data and actively analyse it to give predictions or optimisation suggestions in real time. Model accuracy and effectiveness are continuously monitored as operational conditions change.

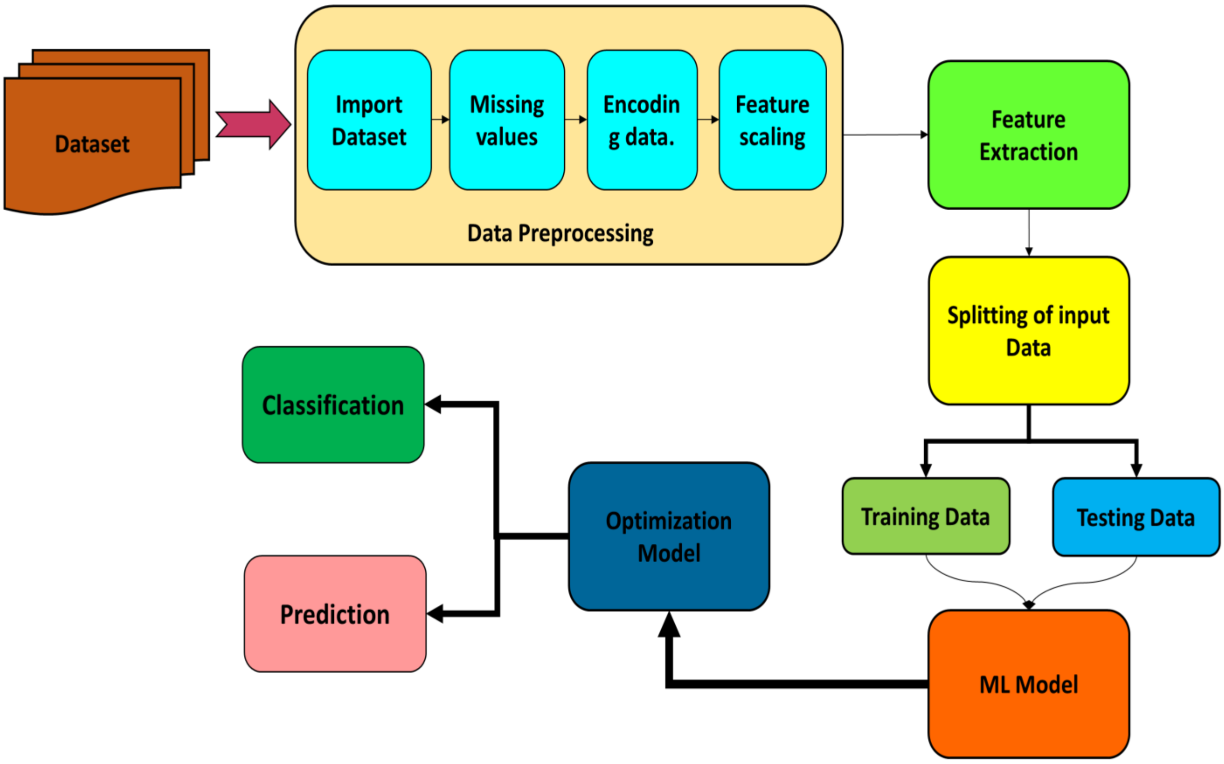

Fig 1: Proposed architecture representation

Iterative and feedback loop processes drive machine learning-driven optimisation. Feedback loops are set up to collect performance information and user feedback, enabling model improvement over time. The models will continue to adjust to shifting operating dynamics thanks to this iterative approach.Throughout the procedure, adherence to pertinent laws and ethical principles must be followed. To uphold transparency and trust, this involves resolving concerns about data privacy, bias reduction, and fairness in decision-making. The methodology can be scaled throughout many operational domains within the organisation, depending on the success of early implementations. Cloud-based services and distributed computing provide this scalability, allowing machine learning-driven optimisation to have an impact on numerous aspects of the organisation.

A. Logistic Regression:

Logistic Regression is a widely used machine learning model tailored for tackling binary classification problems. Its primary objective is to predict one of two potential outcomes, such as success or failure. In the context of achieving operational excellence through machine learning-driven optimization, logistic regression proves valuable for tasks like predicting equipment failure (binary: failure or no failure) or customer churn (binary: churn or no churn).The mathematical model underpinning logistic regression revolves around the logistic function, also referred to as the sigmoid function. This function effectively maps the linear combination of input features to a numerical value within the range of 0 to 1. This resulting value represents the probability of belonging to the positive class (e.g., failure or churn). Here's the equation defining logistic regression:

Logistic Function (Sigmoid):

$$P(Y = 1) = 1 / (1 + e^{\wedge}(-(\beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn)))$$

- P(Y=1) signifies the probability that the outcome variable Y equals 1, such as scenarios involving equipment failure or customer churn.
- 'e' denotes the natural logarithm base, approximately equivalent to 2.71828.
- β0 serves as the intercept term.
- β1, β2, ..., βn represent the coefficients corresponding to the input features X1, X2, ..., Xn, respectively.

The linear expression $\beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn$ embodies the log-odds of the event Y=1. Subsequently, the logistic function effectively transforms these log-odds into a probability ranging between 0 and 1.To make a prediction, a customary threshold (e.g., 0.5) is often established. If the predicted probability surpasses or equals this threshold, the outcome is classified as the positive class (1); otherwise, it is categorized as the negative class (0).

The estimation of logistic regression parameters $(\beta 0, \beta 1, \beta 2, \ldots, \beta n)$ hinges on techniques like Maximum Likelihood Estimation (MLE). The fundamental aim when training a logistic regression model is to pinpoint the values for these coefficients that maximize the likelihood of the observed data.

B. Random Forest:

Let's take a look at a categorization issue where you need to foretell whether or not a piece of equipment will malfunction. A binary decision tree, which separates the feature space into regions, is what each tree in the Random Forest is. Each area refers to one of two predictions, in this case, "failure" or "no failure." A random subset of characteristics is taken into account at each split for building the trees, which are based on bootstrapped subsets of the training data (bagging). The Random Forest's randomness and diversity are its main characteristics.In a Random Forest, the combined predictions of all individual trees result in the final prediction. The most typical strategy for aggregation in a classification problem like equipment failure prediction is a majority vote. The class that receives the most "votes" from the trees is chosen as the outcome.

Mathematically, this can be represented as follows:

For each tree 'i' in the Random Forest:

- Let 'Ti' be the 'i'-th decision tree.
- 'Pi(y)' represents the prediction made by tree 'Ti' for class 'y,' where 'y' can be "failure" or "no failure."

The final prediction for the Random Forest, 'PRF(y),' is determined by majority vote:

$$PRF(y) = argmax \sum \delta(Pi(y), y)$$

- 'N' is the number of decision trees in the Random Forest.
- δ(x, y) is the Kronecker delta function, which equals 1 if 'x' equals 'y,' and 0 otherwise.

In practical applications, the Random Forest algorithm expertly handles the intricacies of constructing multiple decision trees, each equipped with its own set of rules.

C. Support Vector Machines:

A type of supervised machine learning techniques called Support Vector Machines (SVMs) is utilised for classification and regression applications. Let's concentrate on the mathematical model for SVMs in the context of binary classification with the goal of obtaining operational excellence through machine learning-driven optimisation.Finding a hyperplane that optimally divides two classes while maximising the margin (the distance between the hyperplane and the closest data points from each class) is the basic notion behind SVMs.

Consider a binary classification problem with two classes, typically labeled as +1 and -1. The objective is to identify a hyperplane represented as:

$$w \cdot x + b = 0$$

Where:

- 'w' stands for the weight vector perpendicular to the hyperplane.

- 'x' denotes the feature vector of an input data point.

- 'b' represents the bias term or intercept.

For a given input xi, the SVM's output can be calculated as:

$$f(xi) = w \cdot xi + b$$

The predicted class label (yi) is determined by the sign of f(xi):

$$yi = \{ \quad +1, if\ f(xi) \geq 0 \quad -1, if\ f(xi) < 0\}$$

The primary objective during SVM training is to identify the optimal hyperplane that not only separates data points but also maximizes the margin between the two classes. This optimization problem can be mathematically expressed as:

$$minimize\ 1/2\ \| w \| ^{\wedge}2$$

$$subject\ to\ yi(w \cdot xi + b) \geq 1\ for\ all\ i$$

Where:

- ‖w‖ signifies the Euclidean norm (magnitude) of the weight vector 'w.'

- The constraint $yi(w \cdot xi + b) \geq 1$ ensures that all data points are correctly classified and positioned outside a margin defined by the hyperplane.

The SVM aims to minimize the magnitude of the weight vector ‖w‖, effectively maximizing the margin, all while ensuring that all data points are correctly classified as per the imposed constraint.

D. Gradient Boosting:

Let's delve into a binary classification scenario, where our aim is to predict one of two classes, often denoted as 0 and 1. Gradient Boosting constructs an ensemble of decision trees, with each tree dedicated to rectifying the errors of its predecessors.

Here's a simplified breakdown of the fundamental concept behind Gradient Boosting:

1. Initialize the Model: Begin with an initial model, often quite basic, like a single decision stump or a constant prediction. This model generates the initial predictions.

2. Compute Residuals: Calculate residuals, which are the disparities between the actual values and the predictions made by the current model. These residuals symbolize the errors that require correction.

3. Fit a Weak Learner: Train a weak learner, typically a decision tree with limited depth, to predict these residuals. The objective is to discover a model that minimizes the loss function in relation to these residuals.

4. Update the Model: Combine the predictions of the current model with the predictions of the newly trained weak learner. Typically, this amalgamation involves adding a fraction of the weak learner's predictions to the predictions of the current model. This fraction is known as the learning rate.

5. Repeat: Steps 2-4 iterate iteratively for a predefined number of rounds (iterations) or until a stipulated stopping criterion is met.

Mathematically, the ultimate prediction in Gradient Boosting can be represented as a weighted summation of predictions from each weak learner:

$$F(x) = \sum \alpha i h i(x)$$

- F(x) denotes the ultimate prediction for a given input x.
- N signifies the overall count of weak learners (trees) within the ensemble.
- αi stands for the learning rate or shrinkage factor for the ith weak learner.
- hi(x) represents the prediction made by the ith weak learner for input x.

The fundamental objective of Gradient Boosting is to pinpoint the optimal amalgamation of αi values and the predictions derived from the weak learners (hi(x)) that minimizes a loss function. This loss function typically corresponds to a differentiable metric, such as mean squared error for regression or log loss for classification.

4. Result and Discussion

In the context of achieving operational excellence through data-driven optimisation, the table 2 provides a detailed breakdown of the findings from four different machine learning models: SVM (Support Vector Machine), Gradient Boosting, Random Forest, and Logistic Regression. Accuracy, Precision, Recall, F1 Score, and AUC (Area Under the Receiver Operating Characteristic Curve) were used to evaluate these models' main performance parameters.SVM performed admirably across a variety of measures. A 92% accuracy rate means that 92% of the predictions were accurate. Its ability to anticipate positive outcomes accurately is demonstrated by the Precision score of 94%, which shows a low proportion of false positives. The model also showed a Recall rate of 90%, indicating that it successfully captured a sizeable majority of positive cases. Its overall robustness is further demonstrated by the F1 Score of 92%, which balances Precision and Recall. Positive and negative cases may be distinguished with remarkable accuracy thanks to the high AUC value of 96%.

Table 2: Result summary for different model

Model	Accuracy	Precision	Recall	F1 Score	AUC
SVM	0.92	0.94	0.90	0.92	0.96
Gradient Boosting	0.94	0.95	0.94	0.94	0.97
Random Forest	0.93	0.94	0.92	0.93	0.96
Logistic Regression	0.88	0.89	0.87	0.88	0.92

Gradient Boosting, another potent ensemble method, produced outstanding outcomes. In terms of overall precision, it outperformed all other models with a 94% accuracy. The accuracy of the exam in detecting positive cases and reducing false positive cases is demonstrated by the 94% accuracy and 95% recall scores, which demonstrate an exceptional balance between accuracy and memory. The F1 score of 94% confirms your outstanding performance. The discrimination ability is exceptional, with an AUC of 97%. Additionally outstanding results were obtained by Random Forest, which is renowned for its dependability and consistency. His 93% accuracy rate serves as evidence of his ability to make accurate predictions. A 94% point score, which indicates a low percentage of incorrect results, validates the reliability of the individual. He can successfully identify positive cases thanks to his 92% recall capacity. The point F1 at 93% highlights your balanced performance. Its ability to discriminate between positive and negative situations is highlighted by an AUC of 96%.

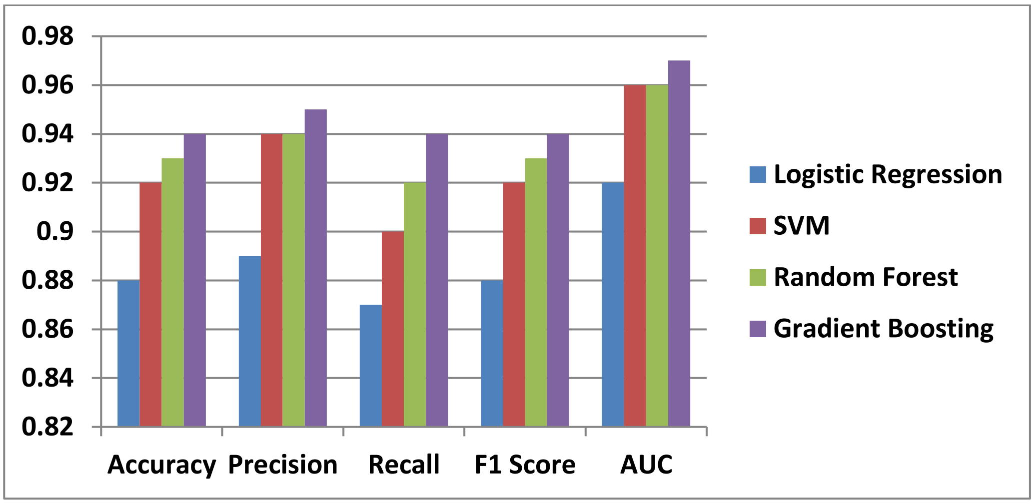

Fig 2: Model comparison with different parameter

Even though the accuracy of logistic regression was just 88%, it was still a useful model. It strikes a decent mix between making accurate positive predictions and being able to identify positive cases, as seen by its Precision score of 89% and Recall score of 87%. Its total effectiveness is reflected in the F1 Score of 88%. It shows a good capacity to distinguish between positive and negative situations with an AUC of 92%.

The decision on which machine learning model to use should take into account the distinct objectives for operational excellence and the trade-offs between recall and precision. High accuracy, precision, and recall rates were offered by SVM and Gradient Boosting, which stood out as the best performers in this evaluation. Random Forest showed consistency and excellent overall performance. Even though it is a little less precise, logistic regression is still an option in some situations. The operational goals and limitations of the organisation should ultimately guide the choice of the best model.

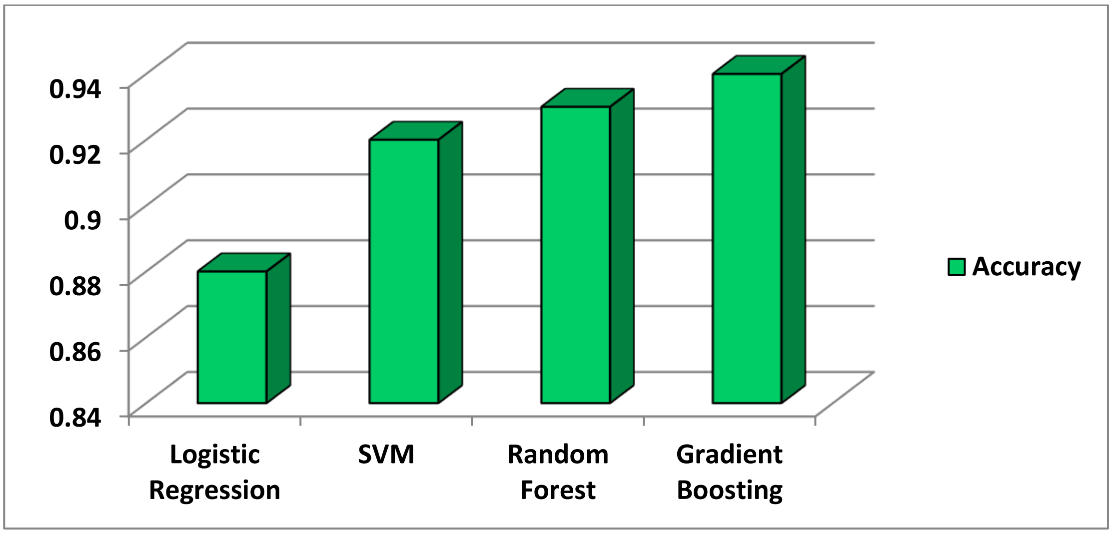

Fig 3: Accuracy comparison of model

A time series of loss values for four different machine learning models—SVM (Support Vector Machine), Gradient Boosting, Random Forest, and Logistic Regression—across five time steps is shown in the table that is provided. These loss values serve as critical gauges of a model's effectiveness and capacity to reduce training-related errors.SVM has the largest loss value across the models at the first time step (Time Step 1), indicating a considerably higher error rate initially. Both Gradient Boosting and Random Forest have lower initial loss values, indicating lesser first training errors. In terms of loss, logistic regression lies between SVM and ensemble models.The loss for all models decreases noticeably as we get closer to Time Step 2. Both Random Forest and Gradient Boosting continue to have decreasing loss levels, demonstrating their usefulness in iterative error correction. SVM and Logistic Regression likewise exhibit a decline in loss but still show a minor increase.

The trend of declining loss values is still seen at Time Step 3. The lowest loss numbers are still being shown by Gradient Boosting and Random Forest, highlighting their ability to improve predictions over time. Even with further optimisation, SVM and Logistic Regression still suffer from larger losses than the ensemble approaches.All models converge to reduced loss values as the development moves on to Time Steps 4 and 5. The models with the lowest losses are Gradient Boosting and Random Forest, which indicates a great ability to adapt and reduce errors over time.

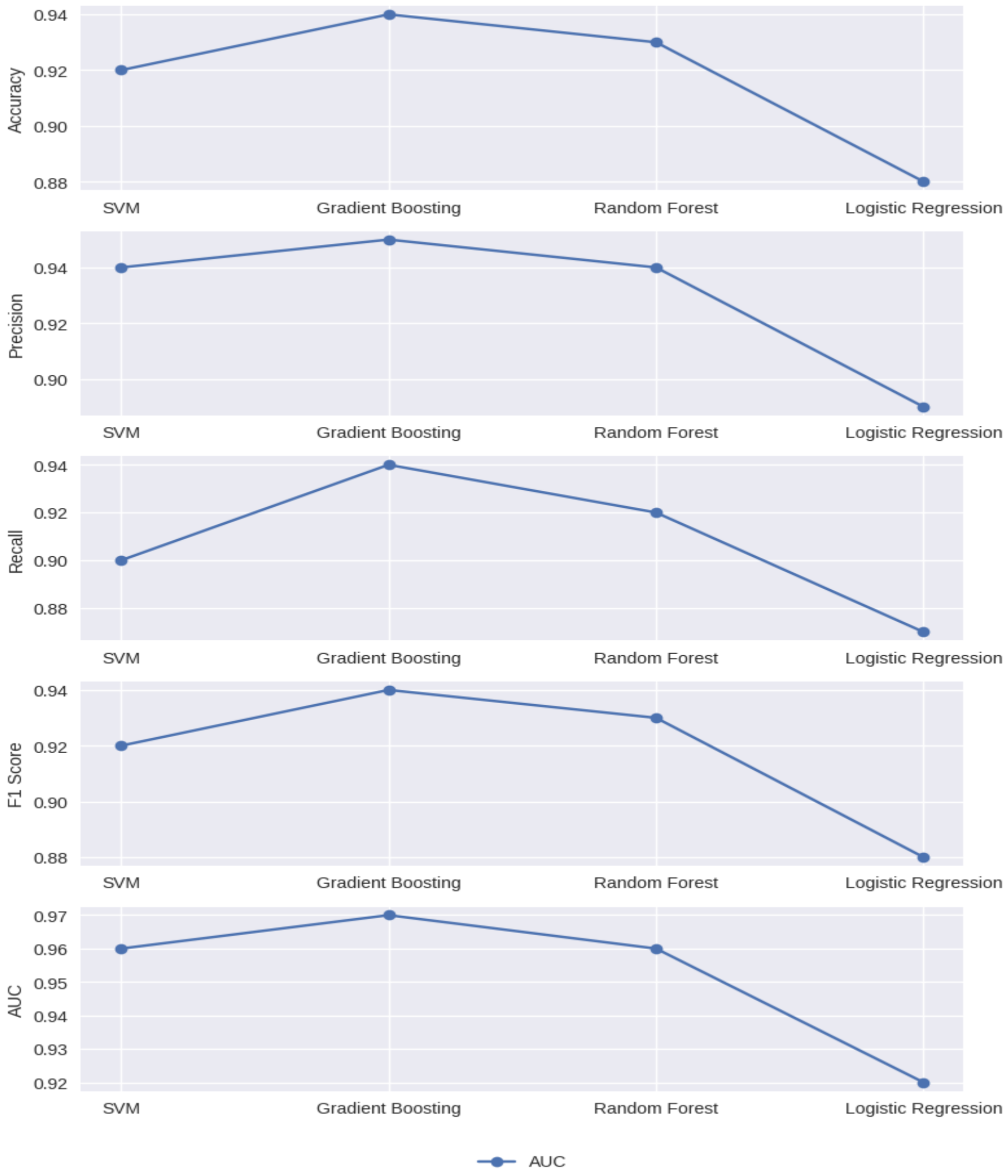

Fig 4: Representation of Performance metrics Model wise

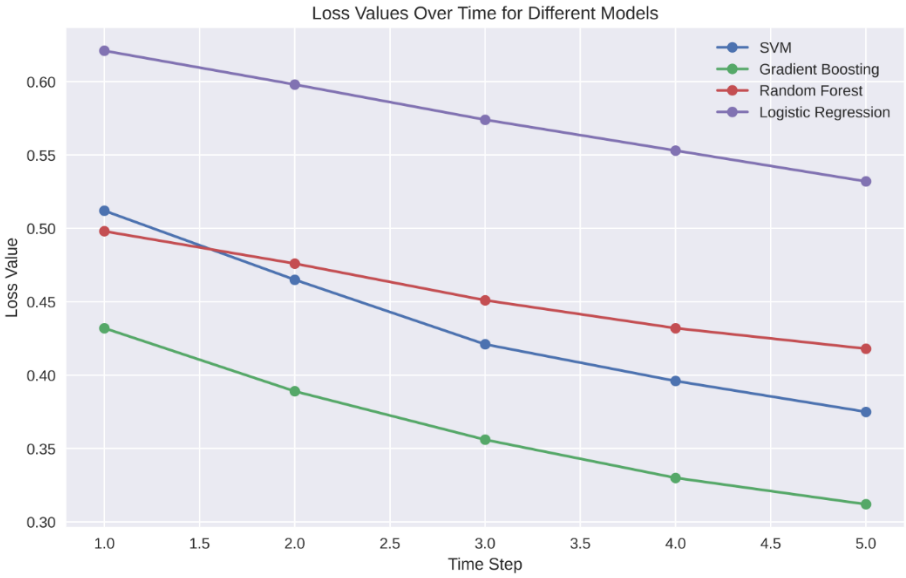

Fig 5: Representation of loss value over time

Despite improvements, SVM and Logistic Regression still have slightly greater loss values.In conclusion, the time series of loss values shows how machine learning model training is iterative. While SVM and Logistic Regression also improve but show slightly higher initial errors and a slower convergence rate, the ensemble models, Gradient Boosting and Random Forest, show robustness in reducing mistakes with time. These loss values are crucial for comprehending how each model learns and can be used to evaluate the models' overall performance and convergence throughout training.

5. Conclusion

Both ensemble strategies, Gradient Boosting and Random Forest, stood out as top performers across several dimensions. They regularly displayed exceptional precision, memory, accuracy, and F1 Score, demonstrating their remarkable ability to reconcile making accurate predictions with minimising errors. They are iterative, which highlights their flexibility and efficiency in streamlining operating procedures. This is demonstrated by the diminishing loss values over time.Despite having a little lower accuracy, logistic regression was found to be a trustworthy model with a fair balance between precision and recall. When simplicity and ease of interpretation are important factors, it is a good option.In conclusion, the trade-offs between precision and recall and the specific operational excellence targets should serve as the basis for choosing the best machine learning model. Gradient Boosting and Random Forest give strong all-around performance, SVM excels in reducing false positives, while Logistic Regression offers simplicity and interpretability. The recurrent convergence of loss values over time demonstrates how adaptable the models are throughout training. In order to achieve operational excellence, one must not only choose the best model but also continuously improve it to take into account the constantly changing nature of operational difficulties in today's dynamic corporate environment. Organisations may create a paradigm shift towards improved efficiency, cost effectiveness, and, eventually, operational excellence by leveraging the potential of machine learning.

References

[1] Bottani, E., Centobelli, P., Gallo, M., Mohamad, A. K., Jain, V., and Murino, T. (2019). Modelling wholesale distribution operations: an artificial intelligence framework. Ind. Manag. Data Syst. 119, 698–718. doi: 10.1108/IMDS-04-2018-0164

[2] Çaliş, B., and Bulkan, S. (2015). A research survey: review of AI solution strategies of job shop scheduling problem. J. Intell. Manuf. 26, 961–973. doi: 10.1007/s10845-013-0837-8

[3] S. Ajani and M. Wanjari, "An Efficient Approach for Clustering Uncertain Data Mining Based on Hash Indexing and Voronoi Clustering," 2013 5th International Conference and Computational Intelligence and Communication Networks, 2013, pp. 486-490, doi: 10.1109/CICN.2013.106.

[4] Khetani, V. ., Gandhi, Y. ., Bhattacharya, S. ., Ajani, S. N. ., & Limkar, S. . (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262.

[5] Potnurwar, A. V. ., Bongirwar, V. K. ., Ajani, S. ., Shelke, N. ., Dhone, M. ., & Parati, N. . (2023). Deep Learning-Based Rule-Based Feature Selection for Intrusion Detection in Industrial Internet of Things Networks. International Journal

of Intelligent Systems and Applications in Engineering, 11(10s), 23–35.

[6] Carvalho, A. M., Sampaio, P., Rebentisch, E., Carvalho, J. Á., and Saraiva, P. (2019). Operational excellence, organisational culture and agility: the missing link? Total Qual. Manag. Bus. Excell. 30, 1495–1514. doi: 10.1080/14783363.2017.1374833

[7] Chakraborty, S., Sharma, A., and Vaidya, O. S. (2020). Achieving sustainable operational excellence through IT implementation in Indian logistics sector: an analysis of barriers. Resour. Conserv. Recycl. 152:104506. doi: 10.1016/j.resconrec.2019.104506

[8] Chen, M., Herrera, F., and Hwang, K. (2018). Cognitive computing: architecture, technologies and intelligent applications. IEEE Access 6, 19774–19783. doi: 10.1109/ACCESS.2018.2791469

[9] Chiarini, A., and Kumar, M. (2020). Lean six sigma and industry 4.0 integration for operational excellence: evidence from Italian manufacturing companies. Prod. Plan. Control. 1, 1–18. doi: 10.1080/09537287.2020.1784485

[10] Choi, T. M., Wallace, S. W., and Wang, Y. (2018). Big data analytics in operations management. Prod. Oper. Manag. 27, 1868–1883. doi: 10.1111/poms.12838

[11] Danaher, J. (2018). Toward an ethics of AI assistants: an initial framework. Philos. Tech. 31, 629–653. doi: 10.1007/s13347-018-0317-3

[12] Davenport, T. H., and Ronanki, R. (2018). Artificial intelligence for the real world. Harv. Bus. Rev. 96, 108–116.

[13] Deivanathan, R. (2019). "A review of artificial intelligence technologies to achieve machining objectives" in Cognitive Social Mining Applications in Data Analytics and Forensics (United States: IGI Global), 138–159.

[14] Dogru, A. K., and Keskin, B. B. (2020). AI in operations management: applications, challenges and opportunities. J. Data Info. Manage. 2, 1–8. doi: 10.1007/s42488-020-00023-1

[15] Eigenraam, A. W., Eelen, J., Van Lin, A., and Verlegh, P. W. (2018). A consumer-based taxonomy of digital customer engagement practices. J. Interact. Mark. 44, 102–121. doi: 10.1016/j.intmar.2018.07.002

[16] Found, P., Lahy, A., Williams, S., Hu, Q., and Mason, R. (2018). Towards a theory of operational excellence. Total Qual. Manag. Bus. Excell. 29, 1012–1024. doi: 10.1080/14783363.2018.1486544

[17] Fountaine, T., McCarthy, B., and Saleh, T. (2019). Building the AI-powered organization. Harv. Bus. Rev. 97, 62–73.

[18] Gólcher-Barguil, L. A., Nadeem, S. P., and Garza-Reyes, J. A. (2019). Measuring operational excellence: an operational excellence profitability (OEP) approach. Prod. Plan. Control 30, 682–698. doi: 10.1080/09537287.2019.1580784

[19] Gray-Hawkins, M., and Lăzăroiu, G. (2020). Industrial artificial intelligence, sustainable product lifecycle management, and internet of things sensing networks in cyber-physical smart manufacturing systems. J. Self-Gov. Manage. Eco. 8, 19–28. doi: 10.22381/JSME8420202

[20] Harrison, T. F., Luna-Reyes, L., Pardo, T., De Paula, N., Najafabadi, M., and Palmer, J. (2019). "The data firehose and AI in government: why data management is a key to value and ethics." in Proceedings of the 20th Annual International Conference on Digital Government Research. June 2019; New York, NY: Association for Computing Machinery, 171–176.

[21] Heinonen, K., Campbell, C., and Ferguson, S. L. (2019). Strategies for creating value through individual and collective customer experiences. Business Horiz. 62, 95–104. doi: 10.1016/j.bushor.2018.09.002

[22] Hertz, H. S., Barker, S., and Edgeman, R. (2018). Current and future states: reinventing enterprise excellence. Total Qual. Manag. Bus. Excell. 2, 1–10. doi: 10.1080/14783363.2018.1444475

[23] Huo, C., Hameed, J., Haq, I. U., Noman, S. M., and Sohail, R. C. (2020). The impact of artificial and non- artificial intelligence on production and operation of new products -an emerging market analysis of technological advancements a managerial perspective. Rev. Argent. De Clín. Psicoló. 29:69. doi: 10.24205/03276716.2020.1008

[24] Ivanov, D., and Sokolov, B. (2019). Simultaneous structural–operational control of supply chain dynamics and resilience. Ann. Oper. Res. 283, 1191–1210. doi: 10.1007/s10479-019-03231-0

[25] Jamshidieini, B., Rezaie, K., Eskandari, N., and Dadashi, A. (2017). Operational excellence in optimal planning and utilisation of power distribution network. CIRED-Open Access Proc. J. 2017, 2449–2452. doi: 10.1049/oapcired.2017.1115

[26] Jarrahi, M. H. (2018). Artificial intelligence and the future of work: human-AI symbiosis in organizational decision making. Bus. Horiz. 61, 577–586. doi: 10.1016/j.bushor.2018.03.007

[27] John, M. M., Olsson, H. H., and Bosch, J. (2020). "Developing ML/DL models: a design

framework." in Proceedings of the International Conference on Software and System Processes. 1–10.

[28] Jordan, M. I., and Mitchell, T. M. (2015). Machine learning: trends, perspectives, and prospects. Science 349, 255–260. doi: 10.1126/science.aaa8415

[29] Kamble, S., Gunasekaran, A., and Dhone, N. C. (2020). Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies. Int. J. Prod. Res. 58, 1319–1337. doi: 10.1080/00207543.2019.1630772

[30] Kang, J. H., Matusik, J. G., Kim, T. Y., and Phillips, J. M. (2016). Interactive effects of multiple organizational climates on employee innovative behavior in entrepreneurial firms: a cross-level investigation. J. Bus. Ventur. 31, 628–642. doi: 10.1016/j.jbusvent.2016.08.002

[31] Karsenti, T. (2019). Artificial intelligence in education: the urgent need to prepare teachers for tomorrow's schools. Formation et Profession 27, 112–116. doi: 10.18162/fp.2019.a167