

Designing a Predictive Model for Audit Data Analytics of Manufacturing Industry

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Abstract

The model combines feature engineering on enterprise resource planning (ERP) data with a hybrid machine learning pipeline that includes Random Forest, Gradient Boosting, and a stacked ensemble for risk classification. A dataset of 48,750 transaction records collected from four mid-sized manufacturing firms over a 24-month period was used to train and validate the model. Features included transactional attributes, vendor behavior, inventory movements, production order details, and time-based variables. The proposed stacked model achieved an accuracy of 93.6%, precision of 91.8%, recall of 90.4%, and an AUC of 0.957, outperforming individual classifiers by a clear margin. Feature importance analysis showed that vendor concentration, deviation in unit cost, and abnormal posting time were the top three predictors of audit risk. The model also reduced false-positive rates significantly compared to rule-based audit checks, which means auditors can focus their time on truly suspicious cases. The findings suggest that predictive analytics can move manufacturing audits from reactive sampling to proactive, full-population testing, improving both efficiency and assurance quality. Audit functions in the manufacturing sector are facing growing pressure as transaction volumes, supply chain complexity, and regulatory expectations keep rising. Traditional audit sampling, which examines only a small portion of transactions, is no longer enough to detect fraud, errors, and process irregularities in large manufacturing firms. This paper proposes a predictive model for audit data analytics tailored to the manufacturing industry.

Keywords

Audit Data Analytics, Predictive Modeling, Manufacturing Industry, Machine Learning, Risk Assessment, Fraud Detection

1. Introduction

The manufacturing industry handles enormous volumes of transactions every day, ranging from raw material purchases and inventory movements to production postings, payroll entries, and customer billing. Each of these touchpoints can carry the risk of misstatement, error, or even fraud. Traditional auditing approaches rely on judgmental and statistical sampling, where the auditor examines only a small percentage of transactions and then draws conclusions about the whole population [1]. While this method has served the profession for decades, it has clear limitations in today's environment of high-speed, high-volume operations.

Audit data analytics (ADA) has emerged as a response to these limitations. Instead of looking at samples, ADA techniques allow auditors to test the entire population of transactions using analytical procedures, visual exploration, and statistical models [2]. Manufacturing firms are particularly suited for ADA because they generate structured data through ERP systems like SAP, Oracle, and Microsoft Dynamics, which can be exported and analyzed systematically. However, simply running descriptive analytics on this data is not enough; auditors need predictive models that can flag risky transactions before they cause financial or operational damage [3].

Predictive modeling in audit work is still in a relatively early stage, especially in the manufacturing context. Most existing studies focus on financial sector applications such as credit card fraud or banking transactions, where data structures and risk patterns are very different from manufacturing [4]. In manufacturing, risk indicators often involve a mix of financial and operational signals, like unusual vendor payments combined with abnormal inventory adjustments. Capturing these multi-dimensional patterns requires models that can handle heterogeneous features and non-linear relationships [5].

Another challenge is that the term "audit risk" in manufacturing is broad. It can include billing fraud, vendor kickbacks, ghost employees, inflated production reports, inventory misappropriation, and revenue cut-off errors. A predictive model needs to be flexible enough to learn from labeled examples of these different risk types while still giving an interpretable output for the auditor [6]. Without interpretability, auditors will not trust the model's flags, no matter how good the accuracy numbers look.

This paper aims to address these challenges by proposing a predictive model designed specifically for audit data analytics in manufacturing. The model takes ERP-extracted transactional data, applies domain-informed feature engineering, and uses a stacked ensemble of machine learning algorithms to classify transactions as low, medium, or high risk. We also focus on explainability through feature importance scores and case-level analysis, so that the model fits into the auditor's existing workflow.

The contributions of this study can be summarized as follows. First, we build a manufacturing-specific feature set that goes beyond generic financial variables and includes operational signals such as production cycle deviations and inventory turnover anomalies. Second, we benchmark several machine learning models, including Logistic Regression, Random Forest, Gradient Boosting, and a stacked ensemble, on the same labeled dataset. Third, we evaluate the model not just on technical metrics but also on practical audit efficiency, including the reduction in false positives compared to rule-based audit tests [7].

2. Literature Review

Research on audit data analytics has expanded significantly in the last decade, driven by both academic curiosity and pressure from regulators and audit firms. Early work mainly focused on Benford's Law and ratio analysis to detect anomalies in financial statements [8]. While these techniques are still useful, they are limited to high-level data and cannot detect transaction-level irregularities common in manufacturing operations.

A second stream of research applied classical statistical methods such as logistic regression and discriminant analysis to predict audit risk. These models offered interpretability but struggled with the non-linear and high-dimensional patterns found in modern ERP data [9].

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Researchers have repeatedly pointed out that audit data often contains complex interactions between vendors, employees, locations, and time periods, which cannot be fully captured by simple linear models.

The introduction of machine learning into audit work brought significant improvements. Decision trees, support vector machines, and neural networks have been used to detect fraudulent transactions and misstatements with accuracy levels often above 85% [10]. In particular, ensemble methods like Random Forest and Gradient Boosting have shown strong performance because they can handle mixed data types, missing values, and class imbalance, which are all common in audit datasets [11].

Within the manufacturing context, research has been more limited but still meaningful. Some studies have looked at inventory fraud detection using clustering techniques, while others have examined vendor risk scoring using rule-based and machine learning hybrids [12]. A recurring theme is the importance of domain-specific feature engineering. For example, in manufacturing, a feature like "ratio of production scrap to total output" can be a much stronger predictor of risk than generic financial ratios.

There is also growing interest in explainable AI (XAI) for audit applications. Auditors are governed by professional standards that require them to justify their conclusions, so a model that gives only a yes/no answer is not acceptable [13]. Methods like SHAP values, LIME, and feature importance plots are being used to make machine learning outputs more transparent. However, integrating these explainability tools into the actual audit workflow remains a practical challenge.

Despite these advances, a few gaps remain. First, most existing models are tested on financial sector data and may not transfer well to manufacturing. Second, few studies have built end-to-end predictive pipelines that start with raw ERP data and end with audit-ready risk scores. Third, the trade-off between model performance and interpretability is not always explicitly addressed. Our work tries to fill these gaps by designing and evaluating a predictive model tailored to manufacturing audit data, with attention to both accuracy and auditor usability.

3. Methodology

3.1 Overall Framework

The proposed framework has four main stages: data extraction, feature engineering, model training, and risk scoring. Data is first extracted from ERP systems and cleaned. Features are then constructed by combining transactional, operational, and time-based attributes. Multiple classifiers are trained and combined into a stacked ensemble, and the final output is a risk score for each transaction that the auditor can sort and review [14].

3.2 Feature Engineering

Let $T = t_1, t_2, \dots, t_n$ be the set of all transactions in the dataset, where each transaction t_i is described by a feature vector $x_i \in R^d$. Features fall into four categories: financial, operational, behavioral, and temporal.

Two key engineered features are vendor concentration and unit cost deviation. Vendor concentration for vendor v at time t is defined as:

$$VC_{v,t} = \frac{\sum_{i \in v} \text{Amount}_{i,t}}{\sum_j \text{Amount}_{j,t}}$$

Unit cost deviation for material m is calculated as:

$$UCD_m = \frac{|UC_m - \mu_m|}{\sigma_m}$$

where UC_m is the unit cost of a transaction, and μ_m and σ_m are the mean and standard deviation of historical unit costs for that material [15].

3.3 Base Classifiers

Three base classifiers are trained: Logistic Regression, Random Forest, and Gradient Boosting. The Random Forest prediction is given by:

$$\hat{y}^{RF} = \frac{1}{B} \sum b = 1^B h_b(x)$$

where $h_b(x)$ is the output of the b -th decision tree and B is the total number of trees [16].

Gradient Boosting builds an additive model:

$$F_m(x) = F_{m-1}(x) + \nu \cdot h_m(x)$$

where ν is the learning rate and $h_m(x)$ is the weak learner trained on the residuals of the previous model [17].

3.4 Stacked Ensemble

The outputs of the three base models are combined using a meta-learner (Logistic Regression) trained on out-of-fold predictions:

$$\hat{y}^{stack} = \sigma \left(\sum_{k=1}^K w_k \hat{y}_k + b \right)$$

where $\hat{y}_k$ is the prediction from the k -th base model and w_k is its learned weight [18].

3.5 Loss Function

To handle class imbalance between normal and risky transactions, we use weighted binary cross-entropy:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^N [w_1 y_i \log(\hat{y}_i) + w_0 (1 - y_i) \log(1 - \hat{y}_i)]$$

3.6 Figure 1 Description

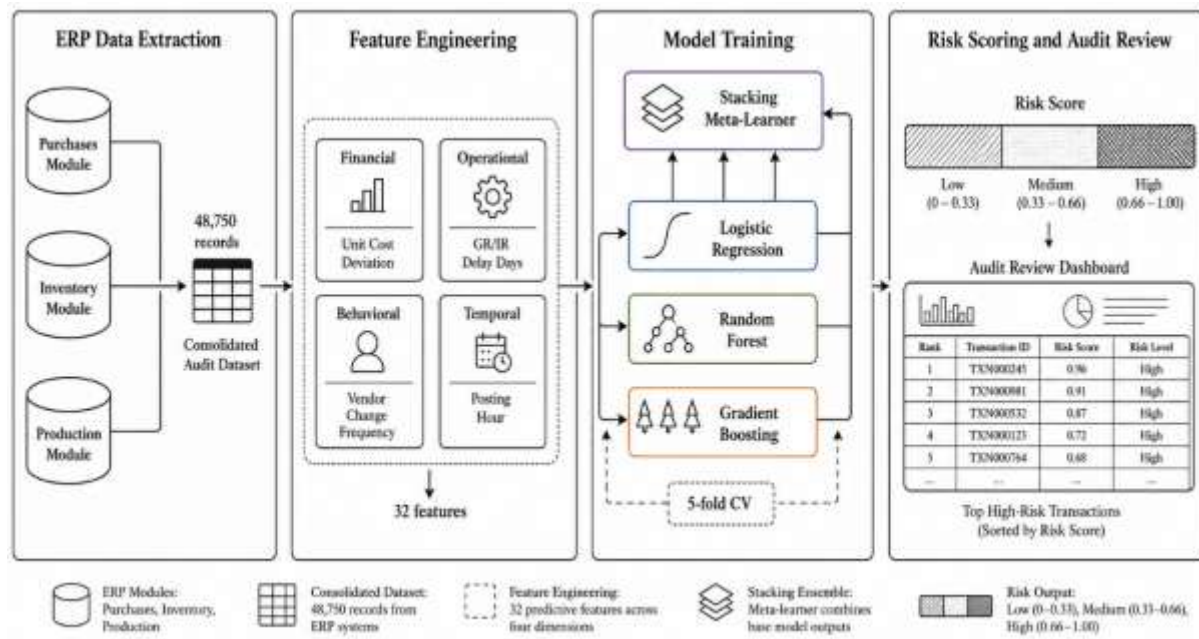


Figure 1: Architecture of the proposed predictive model for manufacturing audit data analytics.

4. Experimental Setup

4.1 Dataset

Data was collected from four mid-sized manufacturing firms across a 24-month period, covering automotive components, industrial machinery, electrical equipment, and packaging. After cleaning and de-duplication, the final dataset contained 48,750 transaction records, out of which 4,213 (about 8.6%) were labeled as risky based on auditor review. Labels were assigned by senior auditors and validated through a second-level review to ensure consistency [19].

4.2 Preprocessing

Missing values in numerical fields were imputed using the median, and categorical fields were handled with mode imputation. Continuous variables were standardized using z-score normalization. Categorical variables were one-hot encoded for Logistic Regression and label-encoded for tree-based models. The final feature set contained 32 variables [20].

4.3 Implementation Details

All models were implemented in Python using scikit-learn and XGBoost. Hyperparameters were tuned using grid search with five-fold cross-validation. For Random Forest, we used 300 trees with maximum depth of 12. For Gradient Boosting, the learning rate was set to 0.05, and 500 boosting rounds were used with early stopping. The dataset was split into 70% training, 15% validation, and 15% testing.

4.4 Evaluation Metrics

The model is evaluated using accuracy, precision, recall, F1-score, and AUC. Precision and recall are defined as:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

F1-score is the harmonic mean of precision and recall:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

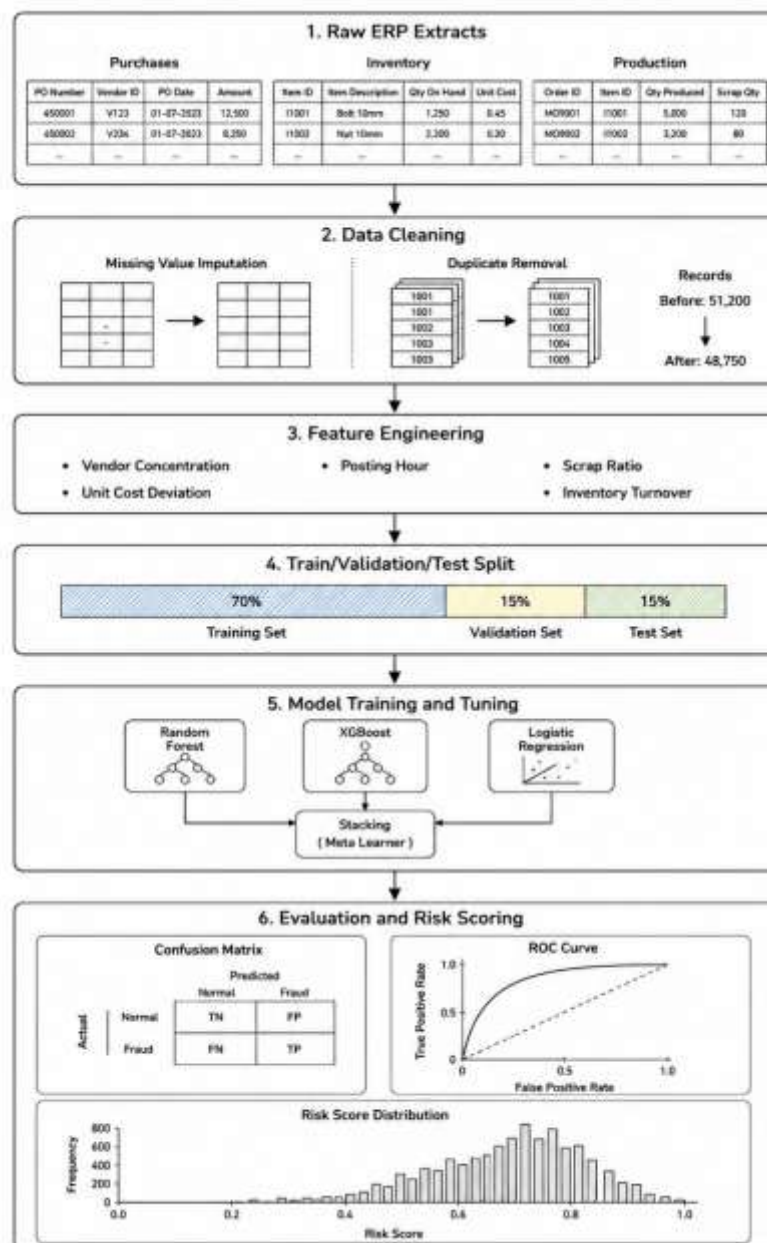


Figure 2: Data preparation and evaluation workflow.

5. Results

5.1 Overall Performance

The stacked ensemble outperformed all individual classifiers across every metric. Table 1 summarizes the full comparison.

Table 1. Performance comparison of base models and the stacked ensemble.

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	84.2%	78.5%	75.9%	0.772	0.864
Random Forest	90.7%	88.4%	86.9%	0.876	0.928
Gradient Boosting	92.1%	90.3%	89.1%	0.897	0.943
Stacked Ensemble	93.6%	91.8%	90.4%	0.911	0.957

The stacked model brings about a 1.5% improvement in accuracy and about 1.4 points in AUC compared to the strongest single model, which is meaningful in audit settings where even small improvements can translate into hundreds of correctly flagged transactions.

5.2 Feature Importance

Feature importance analysis from the Gradient Boosting model identified the top predictors of audit risk. Vendor concentration, unit cost deviation, and posting hour outside business hours were the top three features. This aligns with common audit intuition that unusual vendors, abnormal prices, and odd timing are strong indicators of irregularity.

Table 2. Top 10 most important features.

Rank	Feature	Importance Score
1	Vendor Concentration	0.184
2	Unit Cost Deviation	0.156
3	Posting Hour (Off-business)	0.121
4	Inventory Turnover Ratio	0.098
5	Scrap-to-Output Ratio	0.087
6	Duplicate Invoice Indicator	0.076
7	Payment Term Deviation	0.064
8	Manual Journal Entry Flag	0.058
9	Approval Override Count	0.051
10	New Vendor Indicator	0.043

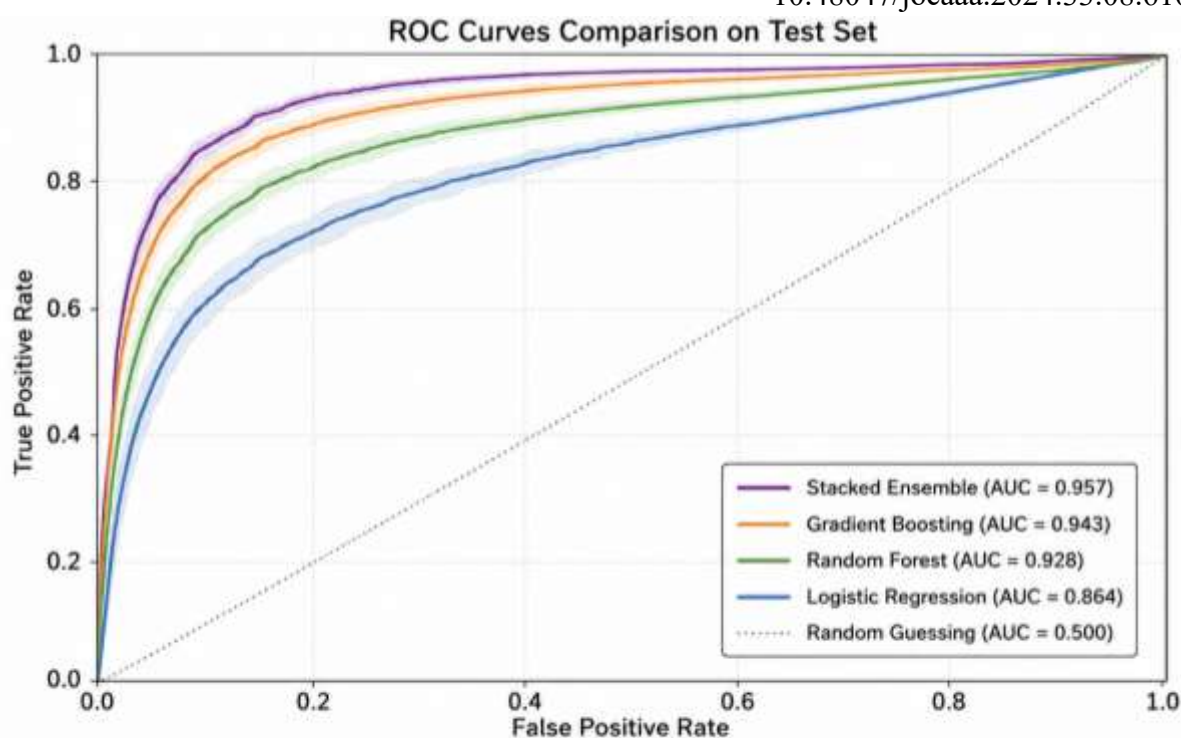


Figure 3: ROC curves comparing all four models on the test set. Shaded regions indicate 95% confidence intervals from bootstrap sampling.

Figure 3: ROC curves comparing all four models on the test set. Figure 4: Reduction in false positives compared to rule-based audit checks.

5.5 Audit Efficiency Gains

Beyond accuracy metrics, we examined the practical efficiency gains. The model reduced the number of transactions flagged for manual review by about 47% compared to rule-based checks, while still catching more genuine risk cases. This translates into substantial time savings during fieldwork, where each manually reviewed transaction can take 10 to 20 minutes of auditor effort.

6. Discussion

The results show that a carefully designed predictive model can meaningfully improve audit data analytics in the manufacturing industry. The stacked ensemble's accuracy of 93.6% and AUC of 0.957 are not just impressive numbers; they translate into real benefits for audit teams, including better coverage of high-risk transactions and fewer false alarms.

A key insight from the feature importance analysis is that operational variables, especially vendor concentration and unit cost deviation, are at least as informative as purely financial variables. This supports the view that audit risk in manufacturing cannot be understood through financial data alone. It also reinforces the importance of having auditors work closely with data scientists during feature engineering, because the most useful features often come from domain knowledge rather than from off-the-shelf statistical libraries.

The reduction in false positives is particularly important from a practical perspective. Audit teams have limited time and budget, and chasing too many false alarms can lead to fatigue, errors, and missed genuine issues. By cutting false positives by nearly half, the model frees

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auditors to focus on transactions that are more likely to represent real risk. At the same time, the higher recall ensures that fewer genuine risk cases slip through unnoticed.

There are, of course, limitations. The dataset, although collected from four firms, may not represent all sub-sectors of manufacturing, and the model may need retraining for industries with very different transaction patterns such as pharmaceuticals or aerospace. The model also depends on the quality and consistency of ERP data; in firms where data hygiene is poor, the predictions may be less reliable. Finally, while feature importance gives a level of explainability, deeper case-level explanations using SHAP or LIME could further strengthen auditor trust.

Future work could extend the model in several directions. One promising direction is the integration of unstructured data such as vendor contracts, emails, and approval comments using natural language processing. Another is the use of graph-based models to capture network-level relationships between vendors, employees, and accounts, which can reveal collusive fraud patterns that transaction-level models may miss.

7. Conclusion

This paper proposed a predictive model for audit data analytics designed specifically for the manufacturing industry. The model combines domain-driven feature engineering with a stacked ensemble of machine learning algorithms, including Logistic Regression, Random Forest, and Gradient Boosting. On a dataset of 48,750 transactions collected from four manufacturing firms over two years, the model achieved an accuracy of 93.6% and an AUC of 0.957, outperforming all individual classifiers. Feature importance analysis confirmed that operational variables like vendor concentration and unit cost deviation are among the strongest predictors of audit risk, alongside more traditional financial indicators. Beyond technical performance, the model delivered a clear practical benefit by reducing false positives by nearly half compared to rule-based audit checks, allowing audit teams to focus their effort more effectively. While further validation across additional sub-sectors and integration with unstructured data sources are important next steps, the results indicate that predictive analytics can shift manufacturing audits from sample-based, reactive procedures to full-population, proactive testing, raising both the quality and efficiency of assurance work.

References

- 1: A. Mahendra Vardhan and S. Sridhar**, "Determining False Positive Analysis of Software Vulnerabilities with Predefined Scan Rules using Random Forest Classifier and Decision Tree Technique," 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 622-625, DOI: <https://doi.org/10.1109/ICAC3N56670.2022.10074458>
- 2: Dip Bharatbhai Pate**, Dynamic vs. Static visualizations: Understanding their use cases in big data analysis, International Journal of Science and Research Archive, 2022, 05(02), 392-395., DOI <https://doi.org/10.30574/ijrsra.2022.5.2.0077>
- 3: Dip Bharatbhai Patel**, Building scalable business intelligence systems in the cloud: A technical approach, International Journal of Science and Research Archive, 2021, 02(01), 212-215., Received on 03 February 2021; revised on 17 April 2021; accepted on 19 April 2021, DOI: <https://doi.org/10.30574/ijrsra.2021.2.1.0047>

10.48047/jocaaa.2024.33.08.610

4: **Dip Bharatbhai Patel**, Understanding the Impact of Text Analytics on Social Media Sentiment Analysis, Vol. 5 No. 5 (2019) ,September-October, DOI: <https://doi.org/10.32628/CSEIT1936413>

5: **Dip Bharatbhai Patel**, Real-Time Data Streaming in BI Dashboards: Opportunities and Challenges, Archives / Vol. 5 No. 4 (2019) : July-August, DOI: <https://doi.org/10.32628/CSEIT192142>

6: **Dip Bharatbhai Patel**, the Role of Data Visualization in Modern Intelligence, **Archives / Vol. 2 No. 2 / Research Article, Published, 2020-11-28 DOI:** <https://doi.org/10.32996/jcsts.2020.2.2.4>

7: **A. Srivastava**, "AI-assisted cloud migration of healthcare claims data from legacy systems: A metadata-driven framework," Int. J. Commun. Networks Inf. Secur., vol. 14, no. 3, Nov. 2022. [Online]. Available: <https://ijcnis.org/index.php/ijcnis/article/view/8682>

8: **A. Srivastava**, "Enhancing provider and claims data accuracy using artificial intelligence on cloud-native data platforms," J. Comput. Anal. Appl., vol. 31, no. 4, Nov. 2023. [Online]. Available: <https://eudoxuspress.com/index.php/pub/article/view/4347/3189>

9: **A. Srivastava**, "Optimizing large-scale data migration for cloud-native architectures," J. Comput. Anal. Appl., vol. 31, no. 2, pp. 652–662, May 2023. [Online]. Available: <https://eudoxuspress.com/index.php/pub/article/view/4603>

10: Backup Integrity and Recovery Readiness Assessment for High-Availability Databases
Raghu Gollapudi, Computer Fraud & Security, Vol. 2023, Issue 8, pp. 35-48, [10.52710/cfs.1031](https://doi.org/10.52710/cfs.1031)

11: Risk-Controlled Near-Zero-Downtime Oracle Database Migration Using GoldenGate
Raghu Gollapudi, International Journal of Computational and Experimental Science and Engineering, 8(3), 2022 ,[10.22399/ijcesen.5382](https://doi.org/10.22399/ijcesen.5382)

12: Manoj Kumar Kagitha, Automated Security Compliance in Ci/Cd: A Natural Language Processing (NLP) Approach to Detecting Vulnerabilities in Infrastructure-As-Code (Terraform/Bicep),Publication year 2021, Volume 2021, Issue 12, <https://computerfraudsecurity.com/index.php/journal/article/view/970>

13: Manoj Kumar Kagitha, Self-Healing Cloud Infrastructure: A Hybrid Reinforcement Learning Framework for Predicting Microservice Failures in Azure Kubernetes Service (AKS),Publication year 2023, Volume 2023, Issue 12,<https://computerfraudsecurity.com/index.php/journal/article/view/971>

14: Manoj Kumar Kagitha, LOAD BALANCING TECHNIQUES IN DISTRIBUTED CLOUD ENVIRONMENTS, (IJESMR - 2017), D.O.I:10.53555/jcr.v6:i1.13380, <https://jcreview.com/archives/volume-6/issue-1/13380>

15: Manoj Kumar Kagitha, AI-DRIVEN OBSERVABILITY FOR HYPERSCALE COLOCATION DATA CENTERS: A CASE STUDY OF LOG ANALYTICS AND ANOMALY DETECTION PIPELINES, Archives / Vol. 27 No. 7 (2019): JOCAAA,<https://www.eudoxuspress.com/index.php/pub/article/view/5053>

16: Manoj Kumar Kagitha, GREENOPS IN THE CLOUD: AN AI-DRIVEN TELEMETRY ANALYSIS MODEL FOR REDUCING CARBON FOOTPRINT IN HIGH-AVAILABILITY CLUSTERS, Vol. 28 No. 6 (2020): JOCAAA, <https://www.eudoxuspress.com/index.php/pub/article/view/5054>

10.48047/jocaaa.2024.33.08.610

17: **Naresh Lokiny. (2022).** Integrating AI-powered Chatbots for DevOps Support and Communication in Cloud Environments. *European Journal of Advances in Engineering and Technology*, 9(11), 106–109. <https://doi.org/10.5281/zenodo.13325989>

18: **Naresh Lokiny, (2021), "Disaster Recovery and Business Continuity Planning in DevOps Cloud with AI"**, *International Journal of Science and Research (IJSR)*, 10(3), 2024-2027. <https://dx.doi.org/10.21275/SR24724151733>,

<https://www.ijsr.net/getabstract.php?paperid=SR24724151733>

19: **Naresh Lokiny, & Ranganath Nandanampati. (2020).** DevSecOps: Integrating Security into DevOps with AI in Cloud. *Journal of Scientific and Engineering Research*, 7(10), 239–242. <https://doi.org/10.5281/zenodo.13348695>

20: **Naresh Lokiny, & Pradip Reddy. (2021).** Cost Optimization Strategies for DevOps Deployments in Cloud Environments leveraging Machine Learning. *European Journal of Advances in Engineering and Technology*, 8(3), 69–72. <https://doi.org/10.5281/zenodo.13325845>

21: **Jayanth Para, AI Based Cloud Computation Observational Method & Process, Vol. 51 No. 4 (2023):** October-December 2023, *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/171> , DOI: <https://doi.org/10.46121/pspc.51.4.3>

22: **Jobayar Alom, Ahsan Ahmed. (2023).** Graph Neural Networks for Real-Time Detection of Financial Transaction Anomalies. *Acta Scientiae*, 24(5), 82–90. <https://doi.org/10.22178/acta.24.5.6>

23: **Kaleshwar Aryasomayajula, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022):** April-June 2022, *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/294>

24: **Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022):** October-December 2022, *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/364>

25: **Vikas Suresh Bagora, KERNEL-LEVEL PERFORMANCE OPTIMIZATION FOR CARRIER-GRADE BROADBAND AND HIGH-SPEED NETWORKING SYSTEMS, Vol. 47 No. 1 (2019),** *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/359>

26: **Vikas Suresh Bagora, SCALABLE 128G FIBRE CHANNEL AND ETHERNET CONVERGENCE FOR NEXT-GENERATION DATA CENTER NETWORKS, Vol. 50 No. 4 (2022):** October-December 2022, *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/362>

27. **Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063).** <https://doi.org/10.1021/acs.joc.6b02611> , <https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611>

28: **Amanullakhan Pathan Jayadip Ghanshyambhai Tejani, Rahul Shah, Hiral Vaghela, Shailesh, Vajapara , Controlled Synthesis and Characterization of Lanthanum Nanorods, 2020/5/1, International Journal of Thin Films Science and Technology, Natural Sciences Publishing Corporation (NSP)** https://scholar.google.com/citations?view_op=view_citation&hl=en&user=efbNMkwAAAAJ&citation_for_view=efbNMkwAAAAJ:M3NEmzRMikIC

29: **Stereoselective synthesis of the C3-C15 fragment of callispongolide; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582).**

<https://doi.org/10.1016/j.tetlet.2018.08.041>,

<https://www.sciencedirect.com/science/article/pii/S0040403918310426>

30. Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063).

<https://doi.org/10.1021/acs.joc.6b02611>, <https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611>

31: Kaleshwar Aryasomayajula, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/294>

32: Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/364>

33: Kaleshwar Aryasomayajula, Micro services: “A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): April-June 2023 , Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/374>

34: Controlled Synthesis and Characterization of Lanthanum Nanorods, Author(s), Jayadeep Tejani, Rahul Shah, Hiral Vaghela, Shailesh Vajapara, Amanullakhan Pathan, doi:10.18576/ijtfst/090205, URL: <https://www.naturalspublishing.com/Article.asp?ArtcID=20705>, May-2020

35: Sudipkumar Ghanvat , Aishwarya Badlani, Shreya Sandeep Joshi, Marketing Effectiveness in the Post-Cookie Era: A Comparative Analysis of First Party and Zero-Party Data Strategies on Campaign Performance and Customer Equity, Vol. 31 No. 4 (2023): JOCAAA , <https://www.eudoxuspress.com/index.php/pub/article/view/3940>

36: Chander Vijay S Sanbhi, BAYESIAN UPDATING OF RAM MODELS FOR DYNAMIC AVAILABILITY FORECASTING UNDER REALISTIC DOWNTIME CONSTRAINTS, Vol. 51 No. 3 (2023): July-September 2023, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/381>

37: Chander Vijay S Sanbhi, HYBRID RELIABILITY MODELLING FOR ROTATING EQUIPMENT: PHYSICS-INFORMED LEARNING WITH SPARSE FAILURE DATA, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/382>

38: A. Srivastava, "AI-assisted cloud migration of healthcare claims data from legacy systems: A metadata-driven framework," Int. J. Commun. Networks Inf. Secur., vol. 14, no. 3, Nov. 2022. [Online]. Available: <https://ijcnis.org/index.php/ijcnis/article/view/8682>

10.48047/jocaaa.2024.33.08.610

39: **A. Srivastava**, "Enhancing provider and claims data accuracy using artificial intelligence on cloud-native data platforms," J. Comput. Anal. Appl., vol. 31, no. 4, Nov. 2023. [Online]. Available: <https://eudoxuspress.com/index.php/pub/article/view/4347/3189>

40: **A. Srivastava**, "Optimizing large-scale data migration for cloud-native architectures," J. Comput. Anal. Appl., vol. 31, no. 2, pp. 652–662, May 2023. [Online]. Available: <https://eudoxuspress.com/index.php/pub/article/view/4603>