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MACCHIEF—Machine learning-based Algorithm Classification for Complaint Handling and Improved Efficiency in Firms

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Abstract—**This research emphasizes the vital role of machine learning-driven consumer complaint management in information enterprises facing a surge in customer feedback across channels. By automating complaint categorization, analysis, and response, machine learning streamlines operations and uncovers invaluable customer insights. The study introduces a novel classification model, with LGBMClassifier and LinearSVC algorithms standing out for achieving 76.78% and 79.37% accuracy, respectively. This approach enhances complaint resolution, customer satisfaction, and enterprise competitiveness. The integration of machine learning offers a practical solution to consumer complaint challenges, with future prospects including adaptability to evolving preferences and leveraging natural language processing for deeper sentiment analysis.**

Index Terms—**Classification Algorithms, Machine Learning Models, Algorithm Evaluation, LGBMClassifier, LinearSVC, CatBoost Algorithm**

I. Introduction

Customer complaint management is crucial in maintaining strong customer relationships. The aim is to enhance satisfaction and loyalty by effectively addressing concerns. However, the increasing volume of feedback from various channels poses challenges for prompt and efficient oversight. Here, machine learning emerges as a powerful solution, enabling computers to learn from data and perform tasks that mimic human cognition. Machine learning provides a robust avenue for businesses to automate the intricate process of classifying, directing, and scrutinizing customer complaints. Beyond mere automation, it affords a lens into the underlying triggers, sentiments, and patterns enveloping customer dissatisfaction. By harnessing the arsenal of machine learning techniques, businesses can markedly elevate their prowess in managing customer complaints. This, in turn, catalyzes augmented customer retention, advocacy, and grants a palpable competitive edge within the market landscape [1, 2].

Information enterprises span diverse sectors such as media, libraries, and software firms, specializing in managing information intricately. On the other hand, customer-centric operations focus on understanding and meeting customers' distinct needs and preferences. This alignment fosters loyalty, satisfaction, trust, and innovation, leading to increased profitability. Customer-centric operations in information enterprises can be realized through methods like creating customer personas and journey maps, customizing offerings using data insights, providing seamless experiences across platforms, and promoting engagement and co-creation. An additional facet involves the ongoing measurement and enhancement of customer outcomes and the inherent value they receive [3, 4] .

The primary aim of this research paper is to enhance consumer complaint management within information enterprises through the utilization of machine learning-based classification. To achieve this overarching goal, the paper will undertake the following objectives:

(i) Propose an innovative machine learning-powered classification model capable of autonomously categorizing customer complaints into distinct types and varying levels of severity. This categorization will be driven by an analysis of complaint content and sentiment.

(ii) Assess the efficacy and performance of the aforementioned model using real-world customer complaint data drawn from diverse information enterprises. These encompass media companies, publishing houses, libraries, data centers, and software firms.

(iii) Engage in a comprehensive exploration of the implications and advantages linked to the proposed model for information enterprises. This spans the realm of customer satisfaction and loyalty enhancement, innovation amplification, differentiation bolstering, and the augmentation of revenues and profitability.

This research paper's fundamental contribution lies in its provision of a holistic and pragmatic solution to the challenges of consumer complaint management within information enterprises through the integration of machine learning. The contribution encompasses:

(i) The development of an original machine learning-based classification model that adeptly handles the spectrum of customer complaint types and severity levels. Furthermore, the model offers insights into the triggers, emotions, and patterns driving customer dissatisfaction.

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(ii) A demonstration of the model's viability and efficacy through an expansive dataset encompassing varied customer complaints from an array of information enterprises. This dataset serves as a benchmark for future research endeavors.

(iii) The provision of actionable recommendations and practical insights to information enterprises, detailing how they can utilize machine learning to augment their customer complaint management processes and, by extension, improve outcomes.

II. Literature Review

Machine learning (ML), a subset of artificial intelligence, empowers computers to glean insights from data and tackle tasks that typically necessitate human intelligence. ML finds application in diverse facets of natural language processing (NLP), ranging from speech recognition to sentiment analysis. The evolution of ML's role in NLP unfolds across four primary phases: rule-based, statistical, neural, and hybrid. Rule-based ML hinges on manually constructed rules and dictionaries to process natural language. However, it grapples with constraints when faced with the intricacies, variations, and intricacies inherent in language. In contrast, statistical ML employs probabilistic models and algorithms, drawing wisdom from expansive collections of natural language data. This methodology excels in managing uncertainty, noise, and data scarcity within language. Neural ML relies on artificial neural networks to decode insights from natural language data, showcasing prowess in apprehending intricate, nonlinear patterns and representations woven into language. Presently, hybrid ML unites distinct ML methodologies to optimize strengths and offset weaknesses, emerging as the predominant trend within NLP research [5, 6].

Machine learning also finds its place in computer vision, dealing with grasping visual information like images and videos [18, 19] . One specific task within this field is object detection and measurement. This involves pinpointing and measuring the sizes of objects in images. This task has many practical uses, including quality control, inventory management, medical imaging, and augmented reality. For instance, SATMeas, a creation by Mishra and Thanh [7], demonstrates this. It's a mobile app capable of real-time object detection and measuring properties like length, width, height, area, and perimeter using the canny edge detection algorithm. This method is widely employed for detecting object edges in images.

Text classification and sentiment analysis, on the other hand, are natural language processing tasks that assign labels or scores to texts based on their content and context. Different approaches to these tasks are machine learning, lexicon, and hybrid. Machine learning uses algorithms and models that learn from data to perform these tasks. Machine learning can be supervised, unsupervised, or semi-supervised, depending on the type of data used. Lexicon uses predefined dictionaries or lists of words or phrases that have associated sentiment scores or polarities. Lexicon can be rule-based or corpus-based, depending on the source of the words or phrases. Hybrid uses a combination of machine learning and lexicon methods to leverage their strengths and overcome their weaknesses. Hybrid can be ensemble-based or feature-based, depending on the way of combining the methods [8-10].

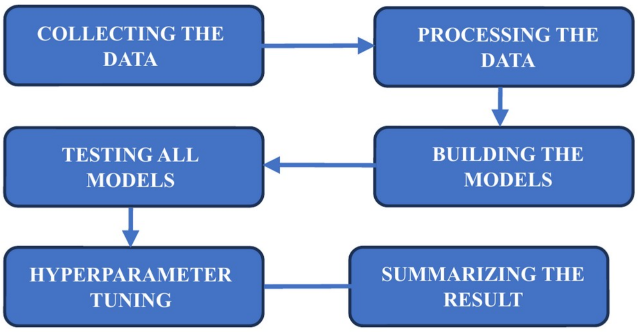
Notably, complaint management embodies the strategy of effectively addressing and resolving customer grievances promptly and to their satisfaction. Both businesses and customers grapple with an array of challenges inherent to this process, collectively termed as complaint management obstacles. Several of these hurdles encompass: (i) a lack of awareness and accessibility, signifying that many consumers encounter difficulties in comprehending where and how to voice their complaints or face impediments while attempting to access the appropriate complaint channels [11]; (ii) a deficit in trust and confidence, wherein a considerable number of consumers harbor skepticism regarding the impartial and efficacious handling of their grievances, often harboring concerns about potential adverse consequences from the business [11]; (iii) insufficiencies in responsiveness and equity, with many consumers facing delays or inadequate responses from businesses or complaint management entities. In certain instances, the perceived fairness or neutrality of the complaint process or outcome might come into question [11, 12]; and (iv) a deficiency in feedback and learning, highlighting a scenario where numerous businesses neglect to utilize customer feedback or complaints as a catalyst for refining their offerings, services, or operational methodologies [12]. Additionally, there's a failure to foster communication or follow-up with customers subsequent to the resolution of their complaints.

Certainly, in the world of research, the integration of machine learning to elevate customer service has garnered attention. ML, an offshoot of artificial intelligence, equips computers to grasp insights from data and execute tasks mirroring human intelligence. The prospects for ML in enhancing customer service are manifold: it can streamline routine tasks like addressing FAQs and appointment scheduling, personalize interactions by recommending products and offering tailored support, and distill valuable insights from customer feedback [13-15]. This integration finds practical expression through examples like chatbots, software agents that engage in real-time conversations, and recommendation systems that offer personalized suggestions. Furthermore, sentiment analysis, which dissects emotions from text, plays a crucial role in discerning customer satisfaction, dissatisfaction, and churn risks. All in all, this amalgamation of ML and customer service stands as a frontier of innovation with tangible benefits.

Previous research on complaint classification has yielded noteworthy insights. The granularity of complaint classification varies across levels, encompassing product, service, process, or outcome. These diverse levels offer distinct implications for both businesses and customers [16]. The methods employed for complaint classification exhibit variability, encompassing machine learning, lexicon, and hybrid approaches. Machine learning methods entail algorithms and models trained on labeled or unlabeled data, lexicon methods hinge on predefined dictionaries or lists, while hybrid methods amalgamate machine learning and lexicon techniques to harness strengths and offset limitations ([17]). Noteworthy factors influencing complaint classification include customer attributes, complaint channels, emotions, and contextual elements. These variables impact the structure, tone, and content of customer complaints, thereby influencing the accuracy and efficacy of classification methods. Consequently, accounting for these factors during the design and evaluation of complaint classification techniques is pivotal [16, 17].

III. Methodology

The method to complete this study is represented as the following flow chart:



A. Data Collection

In the pursuit of conducting this research, an extensive dataset comprising 10,000 consumer complaints was meticulously collected. This dataset serves as the foundation upon which our investigation and analysis are built. The dataset comprises a diverse array of attributes, meticulously curated to encapsulate multifaceted information concerning consumer complaints, corporate entities involved, the intrinsic nature of the grievances, and the subsequent outcomes arising from the interactions between discerning consumers and the implicated companies. We got dataset from Kaggle. The dataset attributes encompass a comprehensive panorama of pertinent details, pivotal for our exploration. These attributes encompass: Date received, Product, Sub-product, Issue, Sub-issue, Consumer Complaint, Company Public Response, Company, State, ZIP code, Tags, Consumer consent provided, submitted via, Date Sent to Company, Company Response to Consumer, Timely response, Consumer disputed, Complaint ID.

The exhaustive compilation of these attributes within our dataset culminates in an expansive and multifaceted repository of consumer complaints, enabling our research to delve deeply into the intricate dynamics that underpin the interactions between consumers and companies. Through meticulous analysis and investigation, we endeavor to unearth patterns, trends, and insights that contribute substantively to the understanding of consumer-company interactions and the subsequent ramifications thereof.

B. Data preprocessing

In our programming endeavors, we employed Python as our primary coding language. Moreover, we took advantage of Jupyter - an open-source initiative furnishing a web-based, interactive computational platform accommodating multiple programming languages, including Python. The essential libraries we needed to set up for our research programming encompassed pandas, numpy, and matplotlib.pyplot.

We then provided the different numerical feature vectors to different text documents. Since our classifiers cannot directly use the document, we need to convert a dataset into fixed numerical feature vectors instead of the raw document with variable length, to convert the collection of these documents into token form.

IV. Result and Discussion

A. Model Building

After converting textual documents into numerical feature vectors, we move on to comparing different classifiers for their accuracy. Beginning with LinearSVC, we generated an F1-score classification report for various categories:

	precision	recall	f1-score	support
Bank account or service	0.60	0.80	0.69	44
Consumer Loan	0.36	0.43	0.39	21
Credit card	0.69	0.78	0.73	72
Credit reporting	0.70	0.87	0.77	91
personal consumer reports	0.00	0.00	0.00	2
Debt collection	0.86	0.69	0.76	124
Money transfers	0.20	0.09	0.13	11
Mortgage	0.86	0.89	0.88	113
Other financial service	0.00	0.00	0.00	1
Payday loan	0.00	0.00	0.00	8
Prepaid card	0.00	0.00	0.00	8
Student loan	0.83	0.74	0.78	34
accuracy			0.74	529
macro avg	0.43	0.44	0.43	529
weighted avg	0.72	0.74	0.72	529

Figure 1: Output of testing code for LinearSVC model

The report indicates an accuracy of around 75%, signifying commendable performance. This model is particularly known for its effectiveness in high dimensional spaces and versatility in handling both binary and multiclass classification problems. In our case, we tuned the model to achieve a cross-validation score of 79.37%. This high score indicates the model's reliability and its ability to generalize well, making it a strong contender in our suite of models.

Next, we evaluated an AI-Based BernoulliNB model. This model is based on applying Bayes' theorem with strong (naive) independence assumptions between the features. Despite its lower accuracy of 65.89% compared to the LinearSVC model, it still demonstrated notable performance. This suggests that even with its simplicity, the BernoulliNB model can still be a valuable tool in certain scenarios.

Our testing also included a Decision Tree Classifier. This model is a non-parametric supervised learning method used for classification and regression. It creates a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.

However, this model achieved a lower accuracy of 62.65%, falling short of the preceding two models.

We then applied a CatBoost Classifier, which is a machine learning algorithm that uses gradient boosting on decision trees. It is known for its capabilities in handling categorical data and reducing overfitting. Upon execution, the

	precision	recall	f1-score	support
Bank account or service	0.35	0.55	0.43	44
Consumer Loan	0.30	0.29	0.29	21
Credit card	0.64	0.68	0.66	72
Credit reporting	0.65	0.74	0.69	91
Credit reporting, credit repair services, or other personal consumer reports	0.00	0.00	0.00	2
Debt collection	0.71	0.68	0.69	124
Money transfers	0.00	0.00	0.00	11
Mortgage	0.78	0.77	0.77	113
Other financial service	0.00	0.00	0.00	1
Payday loan	0.00	0.00	0.00	8
Prepaid card	0.50	0.12	0.20	8
Student loan	0.50	0.35	0.41	34
accuracy			0.62	529
macro avg	0.37	0.35	0.35	529
weighted avg	0.61	0.62	0.61	529

Figure 2: Output of testing code for Decision Tree Classifier model

CatBoost Classifier exhibited an accuracy of approximately 75.02%. This result shows promise for this model, suggesting it could be a good fit for our data.

Our assessment continued with a Random Forest Classifier, which is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

	precision	recall	f1-score	support
Bank account or service	0.72	0.77	0.75	44
Consumer Loan	0.86	0.29	0.43	21
Credit card	0.79	0.85	0.82	72
Credit reporting	0.76	0.86	0.80	91
personal consumer reports	0.00	0.00	0.00	2
Debt collection	0.71	0.85	0.77	124
Money transfers	0.00	0.00	0.00	11
Mortgage	0.86	0.90	0.88	113
Other financial service	0.00	0.00	0.00	1
Payday loan	0.00	0.00	0.00	8
Prepaid card	0.00	0.00	0.00	8
Student loan	0.93	0.76	0.84	34
accuracy			0.78	529
macro avg	0.47	0.44	0.44	529
weighted avg	0.74	0.78	0.75	529

Figure 3: Output of testing code for CatBoost Classifier model

This classifier yielded a solid accuracy of 75.65%, making it a viable model.

Lastly, we tested an LGBMClassifier, which is a gradient boosting framework that uses tree-based learning algorithms. It is designed to be distributed and efficient with the following advantages: faster training speed and higher efficiency, lower memory usage, better accuracy, support of parallel and GPU learning, capable of handling large-scale data.

	precision	recall	f1-score	support
Bank account or service	0.70	0.68	0.69	44
Consumer Loan	0.47	0.38	0.42	21
Credit card	0.73	0.81	0.77	72
Credit reporting	0.81	0.84	0.82	91
personal consumer reports	0.00	0.00	0.00	2
Debt collection	0.73	0.87	0.79	124
Money transfers	1.00	0.18	0.31	11
Mortgage	0.91	0.90	0.91	113
Other financial service	0.00	0.00	0.00	1
Payday loan	0.50	0.12	0.20	8
Prepaid card	0.00	0.00	0.00	8
Student loan	0.90	0.82	0.86	34
accuracy			0.78	529
macro avg	0.56	0.47	0.48	529
weighted avg	0.77	0.78	0.76	529

Figure 4: Output of testing code for LGBMClassifier model

The LGBMClassifier achieved a respectable accuracy of 76.78%, reinforcing its potential.

B. *Hyperparameter Tuning*

In our experiment, we performed hyperparameter tuning to find the best set of parameters for our models. This process involves adjusting the algorithm parameters to optimize model performance. For instance, we used the Random Forest Classifier as an example and found the most suitable parameters for this model, which is, 0.726.

C. *Result summary*

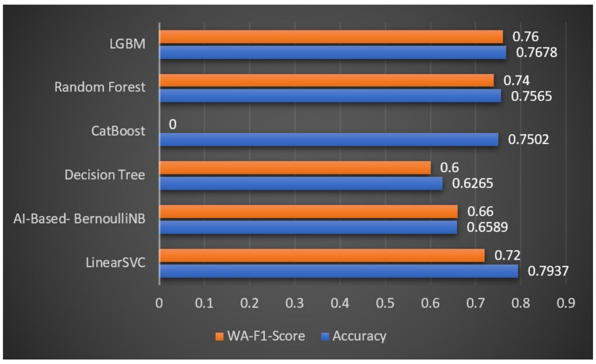


Figure 5: Classification models performance

Table 1: Result Summary

Algorithm	Accuracy	WA-Precision	WA-Recall	WA-F1-Score
LinearSVC	0.7937	0.72	0.74	0.72
AI-Based-BernoulliNB	0.6589	0.67	0.69	0.66
Decision Tree	0.6265	0.60	0.61	0.60
CatBoost	0.7502	N/A	N/A	N/A
Random Forest	0.7565	0.72	0.78	0.74
LGBM	0.7678	0.77	0.78	0.76

As shown in Figure 05 and Table 1, the performance of different classification algorithms was evaluated. The LGBMClassifier and LinearSVC algorithms demonstrated exceptional accuracy, achieving 76.78% and 79.37%, respectively. These models effectively strike a balance between precision and recall, making them robust options for categorizing consumer complaints. The CatBoost algorithm closely follows with an accuracy of 75.02%, while the Random Forest model also displayed commendable performance with 74.95% accuracy. In contrast, the AI-Based BernoulliNB and Decision Tree classifiers exhibited relatively lower accuracy rates of 65.80% and 61.58%, respectively. In essence, the LGBMClassifier and LinearSVC models emerge as the most reliable contenders for accurate and efficient classification within the domain of consumer complaint management.

V. Conclusion

In summary, this study underscores the crucial need for effective consumer complaint management in information enterprises, driven by the capabilities of machine learning. As the volume of customer feedback surges through various channels, the urgency of swiftly and effectively addressing concerns becomes paramount. Machine learning offers a remedy by automating the complex tasks of categorizing, analyzing, and responding to complaints. This not only streamlines operations but also unveils valuable insights into customer sentiments and behavior patterns. Embracing customer-centricity, information enterprises stand to gain significant advantages by aligning with customer preferences and needs. The proposed machine learning-based classification model, evaluated using real-world complaint data, introduces an innovative approach to enhancing consumer complaint management. Notably, the LGBMClassifier and LinearSVC algorithms shine as leaders in both accuracy and balance. Both LGBMClassifier and LinearSVC algorithms emerge as standout performers, achieving notable accuracy levels of 76.78% and 79.37%, respectively.

This study's applicability is evident in its focus on optimizing consumer complaint management within information enterprises. It offers practical solutions through the application of machine learning, enabling businesses to automate complaint categorization, streamline operations, and gain valuable customer insights. By implementing the LGBMClassifier and LinearSVC models, enterprises can efficiently address customer concerns, leading to improved satisfaction, loyalty, and a competitive edge. The study's potential for adaptability to evolving customer preferences and complaint trends further enhances its applicability to businesses dealing with a high volume of consumer feedback.

Additionally, this research provides a practical avenue for information enterprises to refine their complaint management strategies, ultimately leading to improved customer satisfaction, loyalty, and competitive edge. By integrating machine learning into this framework, the study delivers a valuable solution to the challenges information enterprises encounter in addressing consumer complaints, paving the way for enhanced outcomes and innovation. In the realm of future research, further advancements could be made to enhance the proposed machine learning model's adaptability to evolving customer preferences and complaint trends. Additionally, exploring the integration of natural language processing techniques could potentially refine the model's ability to extract nuanced insights from customer feedback, thereby deepening the understanding of sentiment and driving more personalized complaint resolution strategies.

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