International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 03 | March – 2026 DOI: 10.55041/ISJEM05789
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

# AI-Driven Lead Prioritization and CRM Automation using N8N

**Ch. Keerthi[1], Anumalla Varshini[2], Sravanapelly Arun Babu[3], Udharam Sandeep[4], Vangala Madhuri[5]**

[1]Assistant Professor, Department of CSE, Jyothishmathi Institute of Technology and Science, Karimnagar, Telangana, India.

[2]UG Student, Department of CSE, Jyothishmathi Institute of Technology and Science, Karimnagar, Telangana, India.

[3]UG Student, Department of CSE, Jyothishmathi Institute of Technology and Science, Karimnagar, Telangana, India.

[4]UG Student, Department of CSE, Jyothishmathi Institute of Technology and Science, Karimnagar, Telangana, India.

[5]UG Student, Department of CSE, Jyothishmathi Institute of Technology and Science, Karimnagar, Telangana, India.

---

**Abstract –** Customer Relationship Management (CRM) systems are commonly used by organizations to manage customer interactions and support sales activities. In the current digital environment, businesses receive a large number of inquiries from potential customers through channels such as websites, emails, and messaging platforms. These inquiries are usually written in unstructured text form, which makes it challenging to quickly understand customer needs and respond efficiently. Traditional CRM systems mainly focus on storing customer data and tracking interactions but do not provide intelligent analy- sis of incoming messages. This often leads to slow response times, ineffective lead prioritization, and missed business op- portunities. To address this limitation, this study proposes an AI-Driven Lead Prioritization and CRM Automation system implemented using the n8n workflow automation platform. The system applies Natural Language Processing (NLP) and Ma- chine Learning (ML) techniques to analyze incoming lead mes- sages, identify customer intent, and estimate the urgency of the request. Based on these predictions, a priority score is assigned to each lead, allowing the system to automatically trigger work- flow actions such as sending acknowledgment emails, notifying sales teams, scheduling follow-ups, and updating CRM records through API integration. The workflow also tracks the status of leads and supports continuous communication with poten- tial customers. The proposed solution helps reduce manual effort, improves response time, and enhances the efficiency of lead management. In addition, the system is scalable and cost- effective, making it particularly useful for startups and small businesses that want to improve customer engagement through intelligent automation.

***Key Words:*** CRM Automation, Lead Prioritization, Machine Learning, Natural Language Processing, n8n, Workflow Au- tomation, Intelligent CRM.

## 1. INTRODUCTION

Customer Relationship Management (CRM) systems are widely used in modern organizations to manage customer interactions, marketing activities, and sales operations. With the expansion of digital communication channels, businesses now receive a large number of customer inquiries through websites, emails, mobile applications, and social media platforms. These inquiries, often referred to as leads, are usually written in unstructured text form. Because of this, it can be challenging for organizations to quickly understand what the customer is requesting, evaluate the seriousness of the inquiry, and provide a timely response. When responses are delayed or not handled properly, customer satisfaction may decrease and potential business opportunities may be lost.

Most traditional CRM systems mainly serve as platforms for storing customer data, contact information, and records of previ- ous interactions. While these systems help maintain organized customer information, they generally do not include intelligent features to automatically analyze the content of incoming mes- sages or determine their importance. As a result, sales teams must manually review each message, identify the customer's intent, and decide how urgently the request should be handled. This manual approach requires significant time and effort and can also lead to human errors. In some cases, valuable leads may be missed while less important inquiries receive unneces- sary attention, which reduces overall efficiency and slows down the sales process.

Recent developments in Artificial Intelligence (AI) have cre- ated new opportunities for analyzing large volumes of textual data more effectively. Technologies such as Natural Language Processing (NLP) allow computers to interpret and understand human language, while Machine Learning (ML) algorithms can recognize patterns and categorize messages automatically. By applying these techniques, lead messages can be analyzed to identify their intent, such as product inquiry, support request, or pricing information, and their urgency level, such as high, medium, or low priority. This information helps organizations respond more quickly and make better decisions when managing customer inquiries.

Along with intelligent text analysis, workflow automation plat- forms play an important role in improving CRM processes. Platforms like n8n enable different systems and services to be connected so that tasks can be executed automatically. After a lead message is analyzed by the AI model, automated work- flows can update CRM records, notify the sales team, and send

ISSN: 2583-6129
DOI: 10.55041/ISJEM05789

responses to customers without requiring manual intervention. This automation reduces operational workload and ensures that communication with potential customers happens in a timely and consistent manner.

This study presents an AI-driven Lead Prioritization and CRM Automation framework that combines NLP-based message anal- ysis with workflow automation. The proposed system processes incoming lead messages, identifies their intent and urgency, calculates a lead priority score, and automatically routes the lead to the appropriate team for further action. By reducing manual work and enabling faster responses, the system helps improve customer engagement, enhances organizational effi- ciency, and supports more effective decision-making in modern digital business environments.

## 2. Literature Survey

Payne and Frow [1] proposed a strategic framework for im- plementing Customer Relationship Management systems by integrating marketing, sales, and service functions. Their work explains how CRM platforms help organizations organize cus- tomer information and strengthen long-term relationships with customers.

Stone and Woodcock [2] studied digital marketing and customer interaction systems and emphasized that delayed responses and ineffective use of customer data can reduce customer satisfaction and negatively affect conversion rates.

Damania [3] explored the application of Artificial Intelligence in CRM systems, particularly for lead scoring and prediction. The study showed that machine learning models can analyze customer data and help businesses identify and prioritize leads with higher potential value.

Liu [4] introduced sentiment analysis techniques that enable systems to interpret customer opinions and classify the intent of messages. These Natural Language Processing methods help determine whether a message is related to information requests, support queries, or urgent responses.

Abousaber and Abdalla [14] presented AI-based business au- tomation frameworks that support automated communication and real-time decision-making. Their research demonstrated that automation significantly improves operational efficiency and reduces manual effort in business processes.

Devlin et al. [6] introduced BERT, a deep bidirectional trans- former model designed for natural language understanding tasks. Their work showed that transformer-based models significantly improve the performance of text classification and intent detec- tion tasks.

Pedregosa et al. [12] developed Scikit-learn, a widely used ma- chine learning library in Python that supports various techniques such as classification, regression, and clustering. This frame- work enables efficient implementation of predictive models for lead scoring and customer behavior analysis.

Kohavi and Provost [19] examined the role of data mining tech- niques in electronic commerce. Their study highlighted the importance of predictive analytics in identifying high-value cus- tomers and supporting better business decision-making.

## 3. System Architecture

The system architecture is designed as a modular and scalable CRM platform that integrates machine learning techniques with workflow automation to improve lead management. The sys- tem receives incoming lead messages, analyzes their content, determines their priority level, and automatically performs ap- propriate response actions. The architecture is organized into three main components: the Lead Data Collection Module, the AI Analysis Engine, and the Automation and Notification In- terface. The process begins when lead information is collected from different communication channels and continues through intelligent analysis of the message content. Based on the analy- sis results, the system assigns a priority level to each lead and automatically triggers actions such as notifications, responses, and updates to the CRM database. This workflow ensures ef- ficient handling of customer inquiries while reducing manual effort and improving response speed.

### *3.1 System Overview*

The system follows a pipeline-based design where each stage processes the output of the previous one. Incoming messages from web forms, email, and chat are first collected and pre- processed, then passed to the AI analysis engine for classifica- tion. The resulting priority score drives the automation layer, which updates the CRM and dispatches notifications to the sales team.

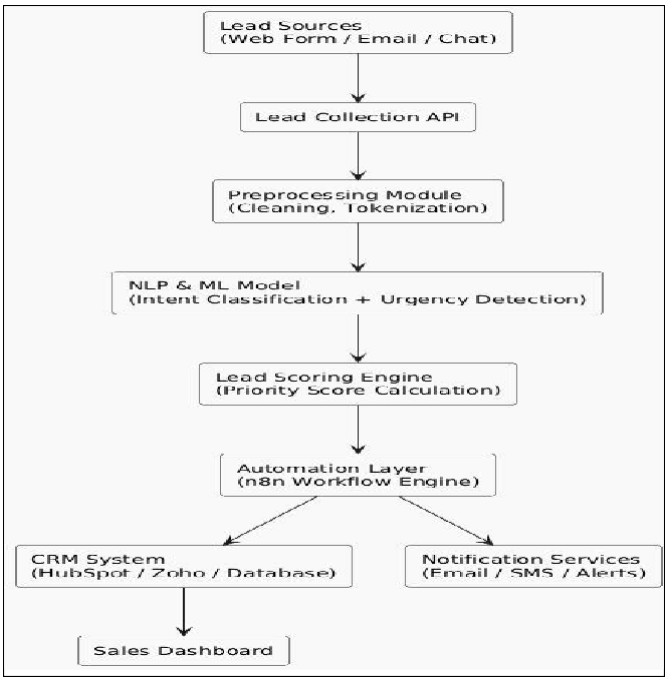


**Figure 1** System Architecture of AI-Driven Lead Prioritization and CRM Automation

### *3.2 Lead Data Collection and Preprocessing Module*

Customer inquiries are gathered from different communication channels such as website forms, emails, and chat applications. These messages are usually written in free-text format and may include different writing styles, abbreviations, spelling varia- tions, or incomplete sentences. Because of this variability, the raw text must be processed before it can be analyzed by machine learning models.

The preprocessing module prepares the collected data through several steps:

- **Data Cleaning:** Unnecessary elements such as special char- acters, HTML tags, and irrelevant symbols are removed from the text.
- **Text Normalization:** All characters are converted to low- ercase and common spelling variations are standardized to maintain consistency.
- **Tokenization:** The text is divided into smaller units such as words or tokens for easier processing.
- **Stop-word Removal:** Frequently used words like "the", "is", and "and", which do not significantly contribute to the mean- ing of the sentence, are removed.

After completing these preprocessing steps, the cleaned text is transformed into numerical feature representations using tech- niques such as TF-IDF or word embeddings. These numerical vectors are then used as input for the machine learning models.

### *3.3 AI-Based Lead Analysis Engine*

The AI analysis engine acts as the central component of the system. It applies Natural Language Processing (NLP) and Machine Learning (ML) methods to interpret the meaning of incoming lead messages and evaluate their level of importance.

The system performs two main prediction tasks:

- **Intent Classification:** Determines the main purpose of the message, such as a course inquiry, pricing request, support query, or request for general information.
- **Urgency Prediction:** Estimates the level of response urgency required for the message, categorizing it as high, medium, or low priority.

For a given input message $M$ , the model predicts the following label set:

$$L = \{Intent,\ Urgency\}$$

A lead priority score is then calculated using a weighted scoring mechanism:

$$Score = w1(Intent) + w2(Urgency)$$

This score helps determine how quickly the lead should be handled and which team should respond.

### *3.4 CRM Integration and Automation Module*

The final module connects the prediction results with the CRM system through the n8n workflow automation platform. Based on the output generated by the AI models, the system automati- cally performs several actions to manage the lead efficiently.

- Automatically storing lead details in the CRM database.
- Forwarding high-priority leads to the appropriate sales repre- sentatives in real time.
- Sending personalized response messages to customers through email or messaging services.
- Generating notification alerts for the sales or support teams.

By automating these processes, the system reduces manual workload, improves response time, and ensures that important leads receive timely attention.

## 4. Methodology

The proposed system operates through an intelligent decision- making process that evaluates incoming customer lead messages and automatically performs appropriate CRM actions. The methodology integrates Natural Language Processing (NLP), Machine Learning (ML), and workflow automation to improve the efficiency of lead management. Initially, the system analyzes the content of the lead message to understand the customer's request and determine its relevance. Based on this analysis, a priority score is assigned to the lead. The system then uses this score to automatically route the lead to the appropriate team and generate suitable responses or notifications. This automated workflow helps organizations respond more quickly to customer inquiries while reducing manual effort and improving overall operational efficiency.

### *4.1 Lead Prioritization Logic*

A key function of the proposed system is the evaluation and prioritization of incoming lead messages. Each message is analyzed using two supervised machine learning models that determine the intent of the inquiry and the urgency of the request. These predictions help the system identify which leads require immediate attention.

- **Intent Classification:** The input message $M$ is first trans- formed into numerical feature vectors using the TF-IDF rep- resentation method. The trained classifier then determines the type of inquiry contained in the message, such as a course in- quiry, pricing request, demo request, or a general information query.

$$\text{Intent} = f1(M)$$

- **Urgency Detection:** A second model evaluates how quickly the message requires a response. Messages that contain words or phrases such as "immediately", "urgent", or "call me now" are more likely to be categorized as high priority.

$$\text{Urgency} = f2(M)$$

- **Lead Score Calculation:** After predicting the intent and urgency, the system calculates a lead score by combining both factors using a weighted formula:

$$Score = w1 \cdot Intent + w2 \cdot Urgency$$

where $w1$ and $w2$ represent predefined weight values assigned to each factor. If $Score > \theta priority$ the lead is considered high priority. This scoring method helps the system distinguish between casual inquiries and leads that show strong potential for business engagement.

### *4.2 Automated CRM Response System*

Once the lead classification process is completed, the system automatically performs the required CRM operations using a Flask-based API and the n8n workflow automation platform. The prediction results generated by the AI models trigger several automated actions designed to handle the lead efficiently.

- **CRM Update:** The system records the lead information along with the predicted intent and urgency results in the CRM database.
- **Automatic Routing:** Leads identified as high priority are im- mediately forwarded to the sales team for further interaction.
- **Email Notification:** A customized response email is automat- ically generated and sent to the customer.

• **Team Alert:** Notifications are delivered to relevant staff mem- bers through email or messaging platforms to ensure timely follow-up.

## 5. Implementation and Setup

An intelligent CRM automation platform was developed to com- bine machine learning models with workflow automation tech- nologies. The implementation includes deploying trained mod- els, enabling communication through APIs, and automatically updating CRM records based on the analysis results. The sys- tem is designed to process incoming lead messages in real time, analyze their content, and determine their priority level. Based on this evaluation, the platform automatically routes leads and triggers appropriate actions without requiring manual interven- tion. This approach improves the efficiency of lead management and ensures faster responses to customer inquiries.

### *5.1 Hardware Configuration*

The proposed system was developed, trained, and tested using a standard computing environment with the following hardware specifications:

• **Processor (CPU):** Intel Core i5 or an equivalent multi-core processor
• **Memory (RAM):** Minimum 8 GB RAM, with 16 GB recom- mended for better performance
• **Storage:** At least 256 GB SSD to store datasets, logs, and application files
• **Network:** Reliable broadband internet connection for API communication and workflow automation
• **Operating System:** Windows 10/11 or Ubuntu Linux

Both the machine learning model training and the API hosting were performed on the same system. Since the dataset primar- ily consists of textual information rather than computationally intensive image data, the use of GPU acceleration was not re- quired.

### *5.2 Software Stack*

The implementation of the system utilizes a combination of programming tools, machine learning libraries, and automation platforms.

• **Programming Language:** Python 3.10 was used for devel- oping the machine learning models and backend services.
• **Machine Learning Libraries:** Scikit-learn was used to build and train classification models for lead analysis.
• **Natural Language Processing:** NLTK and spaCy were ap- plied for text preprocessing tasks such as tokenization and stop-word removal.
• **Data Processing:** NumPy and Pandas were used for handling datasets and performing data manipulation.
• **Model Deployment:** The Flask framework was used to create RESTful APIs for model access.
• **Workflow Automation:** The n8n platform was used to design and manage automated workflows.
• **CRM Integration:** CRM services such as HubSpot or Zoho were connected using their respective APIs.
• **Communication Protocol:** REST APIs and webhooks were used to enable communication between system components.

### *5.3 System Integration*

The trained machine learning model is deployed as a REST API using the Flask framework. Whenever a new lead message is received, the automation workflow forwards the message to the API endpoint for analysis. The API processes the message, predicts the intent and urgency, and generates a lead priority score.

Based on the prediction results returned by the API, the n8n automation engine executes several actions:

• Updating lead details and prediction results in the CRM database
• Sending automated response emails to the customer
• Alerting the sales team about high-priority leads
• Recording prediction outputs for monitoring and performance evaluation

This integrated setup enables real-time message processing, reduces the need for manual handling, and improves the overall efficiency of lead management.

## 6. Results and Discussion

### *6.1 Lead Classification Model Performance*

The intent classification and urgency prediction models were trained using a labeled dataset consisting of customer lead mes- sages collected from email inquiries and website form submis- sions. For model development and evaluation, the dataset was divided into three parts: 70% for training, 20% for validation, and 10% for testing. Textual information from the messages was converted into numerical features using the TF-IDF vec- torization method and then used to train supervised machine learning classifiers.

During the training phase, the models were evaluated across several iterations using commonly used performance metrics including accuracy, precision, recall, and F1-score. The training process showed a gradual reduction in loss values, indicating that the model was effectively learning meaningful patterns from the customer messages.

The intent classification model was able to accurately iden- tify different types of inquiries, such as course-related ques- tions, pricing requests, demo requests, and general information queries. Similarly, the urgency prediction model successfully identified messages that required immediate attention, particu- larly those containing keywords such as *urgent*, *immediately*, and *call back*.

### *6.2 Lead Prioritization Accuracy*

To evaluate the real-world effectiveness, the system was tested on 120 unseen lead messages.

• **True Positives (TP):** 52 high-priority leads were correctly identified.
• **False Negatives (FN):** 5 important leads were classified as medium priority.
• **False Positives (FP):** 6 normal inquiries were incorrectly marked as urgent.

The evaluation metrics were calculated as follows:

$$Precision = \frac{TP}{TP + FP} = \frac{52}{58} \approx 89.6\%$$

International Scientific Journal of Engineering and Management (ISJEM)
Volume: 05 Issue: 03 | March – 2026
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata
ISSN: 2583-6129
DOI: 10.55041/ISJEM05789

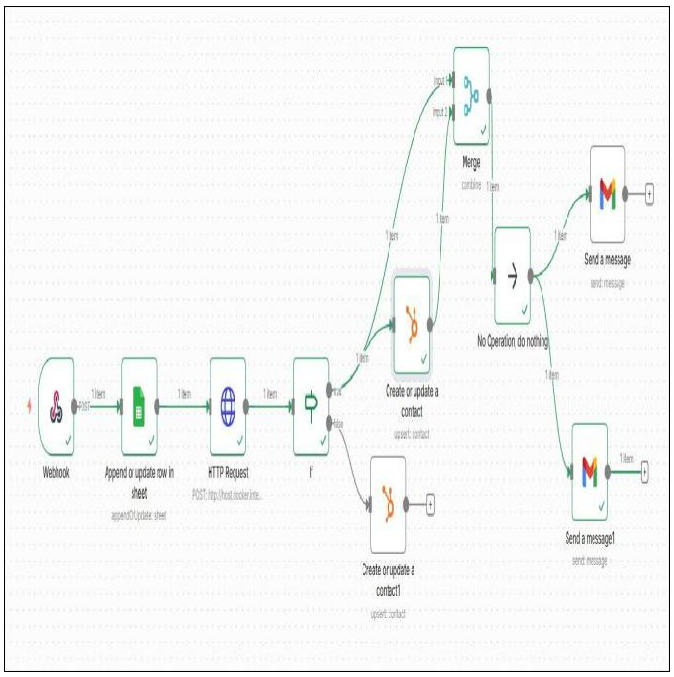


**Figure 2** n8n workflow canvas showing automated lead processing, classification, and notification routing.


**Figure 3** AI Lead Classification Output showing predicted intent, urgency and priority score.

$$Recall = \frac{TP}{TP + FN} = \frac{52}{57} \approx 91.2\%$$

$$F1\text{-}Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \approx 0.904$$

The results show that the system is capable of effectively iden- tifying high-potential customers and distinguishing them from general or low-priority inquiries. This capability helps the sales team focus their efforts on leads that are more likely to convert, thereby improving overall efficiency. The AI model examines each incoming customer message, analyzes its content, and pre- dicts key attributes such as the intent of the inquiry, the level of urgency, and the corresponding priority score assigned to the lead. An example of the generated output is shown in Fig. 3.

### *6.3 Automation Response Time*

A major objective of the system is reducing the response delay between receiving a lead and contacting the customer. The total response time $T_{total}$ is divided into the following components:

$$T_{total} = T_{analysis} + T_{workflow} + T_{notification}$$

where

- $T_{analysis}$ = machine learning model prediction time
- $T_{workflow}$ = n8n automation processing time
- $T_{notification}$ = email/message delivery time The average

measured times were:

- **Text analysis and prediction:** 0.4 seconds
- **Workflow automation execution:** 0.7 seconds
- **Email notification delivery:** 2–5 seconds

The average total response time was approximately 3–6 seconds, which is significantly faster than manual CRM handling, where

### *6.4 Impact on CRM Efficiency*

After implementing the automated workflow, several improve- ments were observed in the lead management process:

responses typically take several hours.

- The amount of manual work required from staff members was significantly reduced.
- Follow-up communication with potential customers became faster and more consistent.
- Lead information was stored and organized more efficiently within the CRM system.

The automated framework ensured that urgent inquiries were handled without being overlooked, which helped improve over- all customer engagement. When compared with the earlier man- ual approach, the automated CRM system reduced the average response delay by more than 80%, demonstrating a significant improvement in operational efficiency.

## 7. Advantages and Limitations

### *7.1 Advantages*

- **Automation:** The system automatically performs lead sort- ing and prioritization tasks, removing the need for manual processing and reducing the chances of delayed responses.
- **Intelligent Lead Scoring:** Machine learning models analyze customer messages to identify intent and urgency, allowing the system to prioritize leads that have higher business poten- tial.
- **Real-Time CRM Integration:** Lead information and predic- tion results are directly updated in the CRM system, and leads are routed to the appropriate team automatically.
- **Improved Response Time:** By using automated workflows, the system is able to respond to customer inquiries within seconds instead of hours.
- **Scalability:** The platform can efficiently manage a large num-

ber of incoming lead messages without requiring additional staff.

- **Cost Efficiency:** Since the system works with existing CRM platforms and automation tools, it reduces the need for expen- sive infrastructure or additional resources.

### *7.2 Limitations*

- **Data Dependency:** The effectiveness of the machine learning models largely depends on the quality and quantity of the labeled training data. If the dataset is limited or contains noisy data, the prediction accuracy may decrease.
- **Keyword Sensitivity:** The urgency detection mechanism may sometimes produce incorrect predictions when customers use uncommon phrases, indirect expressions, or informal language that the model has not encountered during training.
- **Internet Dependency:** The automation workflow requires a stable internet connection for API communication, workflow execution, and sending email notifications.
- **Model Generalization:** The trained models are optimized for the dataset used during training. When applied to a dif- ferent business domain or type of customer inquiries, the performance may decline.
- **CRM API Limitations:** The system integration relies on third-party CRM APIs, and its performance can be affected by API restrictions, rate limits, or service availability.

## 8. Future Scope

The current implementation demonstrates a working proof-of- concept for an intelligent CRM automation system. While the system effectively performs lead analysis and automated response generation, several enhancements can further improve its functionality and enable deployment in large-scale enterprise environments.

- **Advanced NLP Models:** Future versions of the system can integrate more advanced deep learning models such as BERT or other transformer-based architectures. These models can improve the accuracy of intent detection and enable the system to better interpret complex or ambiguous customer messages.
- **Multilingual Support:** At present, the system mainly pro- cesses English text. Expanding the platform to support mul- tiple languages will allow businesses to analyze customer inquiries written in regional or international languages, mak- ing the system more inclusive and globally applicable.
- **Voice and Chatbot Integration:** The platform can be ex- tended to support voice-based interactions and AI-driven chat- bots. By incorporating speech-to-text conversion and conver- sational AI, the system could automatically process phone inquiries and live chat conversations.
- **Predictive Lead Conversion Analysis:** Future improvements may include predictive analytics that examine historical lead data to estimate the likelihood of customer conversion. Such insights could help sales teams prioritize follow-ups and adopt more effective engagement strategies.
- **Mobile Application Integration:** Developing a mobile in- terface for sales representatives would allow them to receive real-time lead notifications, monitor lead activity, and manage responses directly through their smartphones.
- **Cloud Deployment and Scalability:** Deploying the system on cloud platforms such as AWS or Azure can enable scalable processing of large volumes of leads while maintaining high availability and system reliability.
- **Data Privacy and Security:** Future implementations can in- corporate stronger security mechanisms, including encryption, secure authentication methods, and privacy-preserving prac- tices to ensure compliance with data protection regulations and safeguard customer data.

## 9. Conclusion

This paper presented an AI-based system for lead prioritization and CRM automation that combines Machine Learning and Nat- ural Language Processing with the n8n workflow automation platform. The proposed framework analyzes incoming customer messages to identify their intent and urgency, calculates a lead priority score, and automatically updates the CRM system while notifying the sales team. The experimental evaluation shows that the system improves the accuracy of lead classification and significantly reduces response time compared with traditional manual processing. By supporting real-time lead routing and au- tomated communication, the system helps organizations engage with customers more effectively, reduces the workload on staff, and assists in making faster business decisions. Overall, the proposed solution offers a practical, scalable, and cost-efficient approach for improving customer relationship management in modern business environments.

## Acknowledgement

The authors would like to express their sincere gratitude to the Department of Computer Science and Engineering at Jyothish- mathi Institute of Technology and Science for providing the resources, facilities, and support required to conduct this re- search. The authors also appreciate the contributions of the open-source community whose tools and libraries played an important role in the development and implementation of this system.

## References

[1] A. Payne and P. Frow, “A strategic framework for customer relationship management,” *Journal of Marketing*, vol. 69, no. 4, pp. 167–176, 2005.

[2] M. Stone and N. Woodcock, “Interactive, direct and dig- ital marketing: A future that depends on better use of business intelligence,” *Journal of Research in Interactive Marketing*, vol. 8, no. 1, pp. 4–17, 2014.

[3] D. Damania, “Artificial Intelligence in Customer Relation- ship Management,” *International Journal of Computer Applications*, vol. 178, no. 7, pp. 15–20, 2019.

[4] B. Liu, *Sentiment Analysis and Opinion Mining*. Morgan & Claypool Publishers, 2012.

[5] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient estimation of word representations in vector space,” arXiv preprint arXiv:1301.3781, 2013.

[6] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in *Proc. NAACL-HLT*, 2019, pp. 4171–4186.

[7] F. Chollet, *Deep Learning with Python*. Manning Publica- tions, 2017.

[8] S. Raschka and V. Mirjalili, *Python Machine Learning*. Packt Publishing, 2019.

[9] n8n GmbH, "n8n Workflow Automation Documentation," 2024. [Online]. Available: https://docs.n8n.io/

[10] HubSpot Inc., "HubSpot CRM API Documentation," 2024. [Online]. Available: https://developers. hubspot.com/docs/api/overview

[11] Zoho Corporation, "Zoho CRM Developer API," 2024. [Online]. Available: https://www.zoho. com/crm/developer/docs/api/

[12] T. Pedregosa et al., "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[13] S. Bird, E. Klein, and E. Loper, *Natural Language Pro- cessing with Python*. O'Reilly Media, 2009.

[14] M. Abousaber and M. Abdalla, "Artificial Intelligence Ap- plications in Business Process Automation," *IEEE Access*, vol. 11, pp. 55321–55330, 2023.

[15] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learn- ing*. MIT Press, 2016.

[16] D. Jurafsky and J. H. Martin, *Speech and Language Pro- cessing*, 3rd ed. Pearson, 2022.

[17] P. Jackson and I. Moulinier, *Natural Language Processing for Online Applications*. John Benjamins Publishing, 2007.

[18] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 4th ed. Pearson, 2021.

[19] R. Kohavi and F. Provost, "Applications of data mining to electronic commerce," *Data Mining and Knowledge Discovery*, vol. 5, no. 1-2, pp. 5–10, 2001.

[20] H. Nguyen and T. Simkin, "The dark side of CRM: advan- taged and disadvantaged customers," *Journal of Consumer Marketing*, vol. 30, no. 1, pp. 17–30, 2013.