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Kodein-Penetration: Recommendations of Customer Personalization Level in A CRM using Deep Learning

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Abstract

This study aims to develop a personalization-level recommendation model implemented in the Customer Relationship Management (CRM) system at Kodegiri company, called KodeinPenetration. Personalization in CRM aims to improve customer interaction by providing more relevant recommendations based on their needs and preferences. To achieve this goal, this study tested several classification models using historical customer interaction data as the basis for analysis. The classification models tested included decision tree-based methods such as Random Forest, Gradient Boosting, and AdaBoosting, as well as deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). In addition, two main feature extraction techniques were applied to process text data, namely TF-IDF (Term Frequency-Inverse Document Frequency) and Tokenizer Padding. TF-IDF is used to represent words as numeric vectors based on their frequency of occurrence. In contrast, Tokenizer Padding is used in deep learning models to convert text into a numeric format that neural networks can process. The test results showed that the decision tree-based method using the TF-IDF feature produced the best accuracy of up to 82%. On the other hand, the deep learning model with GRU architecture utilizing Tokenizer Padding achieved the highest accuracy of 88.23%. This shows that the deep learning model has greater potential in handling sequential data and providing more accurate results compared to traditional methods. This study provides an important contribution to the development of deep learning-based personalized recommendation systems in CRM. By leveraging historical customer interactions, this system can improve user experience by offering more relevant and targeted services.

Keywords: CRM, Deep Learning, Economic Growth, Penetration, Personalized, Sequential

1. Introduction

Customer Relationship Management has become a necessity of marketing strategies in various industry sectors, playing an important role in helping companies understand customer needs, build long-term relationships, and increase loyalty [1], [2]. In an increasingly competitive business world, companies are required to provide more personalized and relevant services to their customers [3], [4]. This raises the need for a more sophisticated approach to managing and personalizing interactions with customers. One of the most important aspects of a modern CRM strategy is the level of personalization implemented [5], [6]. The more personalized the customer experience, the greater the opportunity for the company to increase customer engagement and retention. However, the biggest challenge is how to determine the appropriate level of personalization for everyone. The use of conventional marketing techniques based on segmentation is generally based on customer service assumptions, and CRM has yet to be able to maximize its potential.

At Kodegiri company, a technology company engaged in software development, the issue of personalization in CRM has become increasingly urgent. As a technology-based service provider that relies on a large and diverse customer base, Kodegiri company faces challenges in managing the ever-growing volume of customer data. The need for deeper and more targeted personalization is increasingly felt, especially in efforts to penetrate the market and increase customer loyalty. Thus, this study proposes the application of a customer personalization level determination system

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based on customer data classification. By categorizing customers based on their behavior, preferences, and interactions, Kodegiri company can optimize more effective personalization strategies tailored to individual characteristics. This promising approach not only promises to increase customer engagement but also to accelerate the penetration of personalization across the company's customer base, offering a bright future for Kodegiri company.

Previous research has discussed the importance of personalization in CRM and tried to use a variety of approaches, including segmentation-based methods and automated recommendations [7], [8]. However, these methods often use rule-based techniques or static segmentation that are less dynamic in the face of rapid changes in customer behavior. Several studies have explored the application of machine learning and artificial intelligence techniques in CRM [1], [9], [10], especially in building a recommendation system and analyzing customer sentiment. However, there are still significant limitations in the ability of these models to pinpoint specific levels of personalization based on complex and multivariate patterns of customer behavior, highlighting the urgent need for innovative solutions.

To overcome the existing limitations, this study proposes a deep learning-based method to determine the level of customer personalization in CRM at Kodegiri company. Deep learning was chosen because of its ability to handle large, complex, and multivariate data, as well as its ability to extract hidden patterns that machine learning models cannot capture. The model proposed in this study uses a neural network architecture that will be trained to recognize various variables that affect purchase decisions, customer preferences, and interaction behavior with the services provided by Kodegiri company. This model is expected to generate more precise personalization-level recommendations for each customer, allowing Kodegiri company to implement a more effective and efficient CRM strategy.

Therefore, the purpose of this study is to develop a personalization-level recommendation model that can be practically applied in the CRM system at Kodegiri company, named Kodein-Penetration. The results of this study are expected to significantly enhance the effectiveness of our CRM strategies by employing a more targeted and data-based personalization approach. Moreover, this research is anticipated to pave the way for the use of deep learning in various other applications related to customer relationship management, opening up new and exciting opportunities.

2. Related Work

Customer Relationship Management systems play an important role in managing a company's interactions with potential customers. The effectiveness of CRM systems can be significantly improved through the implementation of personalized recommendation models, which leverage customer historical data to tailor marketing strategies and improve customer engagement. Recent advances in machine learning, especially deep learning techniques, have paved the way for more sophisticated personalization strategies in CRM. Personalization in CRM refers to tailoring interactions and offers based on individual customer preferences and behaviors. Research shows that personalized marketing can improve customer satisfaction and loyalty [11]. For example, Amazon's recommendation system, which utilizes collaborative filtering techniques, has been instrumental in driving sales through targeted suggestions [12].

Various Machine Learning techniques have been explored for customer classification and personalization. Random Forest and Gradient Boosting are ensemble methods that have proven effective in handling high-dimensional data [13], [14]. AdaBoosting, as another ensemble method, has been applied in a variety of contexts to improve classification accuracy [15]. These models provide a solid foundation for understanding customer behavior based on historical interactions. However, the rise of deep learning has revolutionized the approach to customer personalization. Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) networks are effective for sequential data analysis, making them suitable for modeling customer interactions over time [16], [17]. Studies show that LSTM models outperform machine learning methods in capturing temporal dynamics of customer behavior, leading to more accurate recommendations [18].

Thus, developing a CRM that integrates artificial intelligence, especially deep learning, offers opportunities to improve customer personalization in CRM systems. By leveraging historical interaction data and applying sophisticated feature extraction techniques, businesses can better understand their customers and tailor their marketing efforts. The proposed CRM model aims to provide a robust framework for personalized recommendations at Kodegiri company.

3. Research Method

Based on the purpose of the research to develop a recommendation model for the level of personalization in the CRM system, the stages of CRM performance, in general are as shown in figure 1, and the stages of building the model, as shown in figure 2. In figure 1, personalization is built through the customer's "activities" history with several attributes such as "Deal Name", "activity type", "frequency activity", and "notes", which later enter these attributes as information to provide a personalization level recommendation to the customer. So that when potential customers are in a certain label, they will be categorized in the status of "Deals" with the categories "Cold", "Warm", "Hot", "Deal", and "Lost" through the details as in table 1.

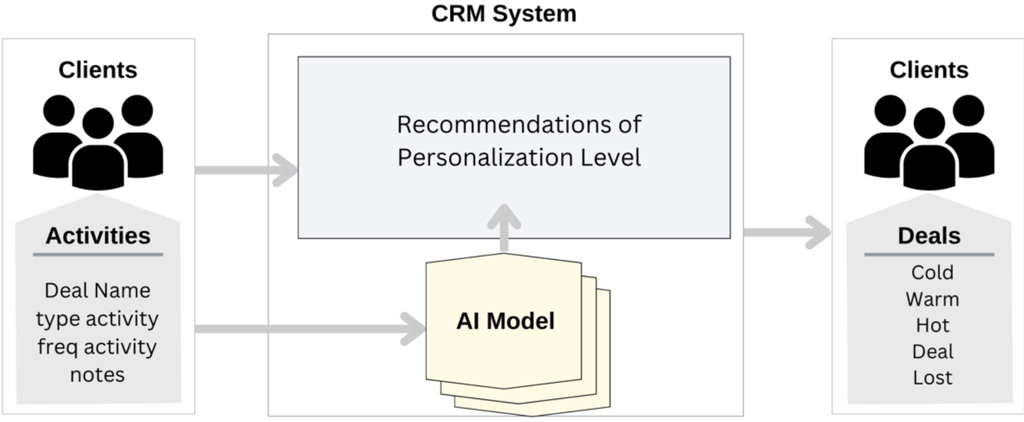

Figure 1. Flow of CRM Performance in Penetration Levels.

Table 1. Customer Level Conditions

Customer Level	Description
Cold	Consumers who have interacted but have been inactive for a certain period
Warm	Consumers who have shown interest and previous interactions, such as visiting a site or signing up
Hot	Consumers who are very interested and ready to make a purchase
Lost	Consumers who were previously active but have not interacted or made a purchase for a long time
Deal	Label deals are only for projects that have been agreed upon by both parties and are just waiting for the payment process

In figure 2, the process begins with data collection and pre-processing. After that, the feature extraction and modeling stage. Finally, model evaluation is carried out by measuring the performance of each model using confusion metrics such as accuracy, precision, and recall to determine the most effective model in classifying customers into relevant classes.

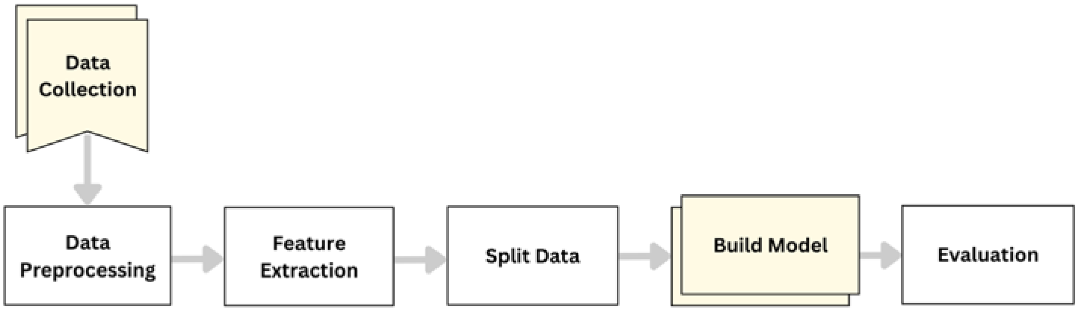

Figure 2. Flow Builds Artificial Intelligence Models at the Customer Level.

3.1. Data Collection

The data for this study was collected from Kodegiri company's Customer Relationship Management system. The data collected includes historical customer interactions, i.e., activities, including the type of interaction, frequency of interaction, and customer responses recorded in system records. The data is downloaded from the CRM system in the form of an Excel file for further analysis. In the data collection process, data is also merged from several activities related to customer history. The result of the merged dataset is shown in figure 3.

Deal Name	Stage	Label	Reason	Amount	Expected Closed Date	Tags	Owner_x	Companies_x	...	No_y	Title	Type Activity
Sales Training (Volvo Cars)	INITIAL MEETING/CALL	COLD	Tidak cocok dengan Custom Development/tidak di...	-	2024-01-01	NO TAG	KRM	Volvo Cars	...	60.0	First Meeting menggali kebutuhan	TASK
Pembuatan Logo - ERA JAYA	INITIAL MEETING/CALL	NaN	NaN	Rp12.500.000,00	2024-06-30	NO TAG	DEL	ERA JAYA	...	4.0	update follow up	TASK
Software Seni (Bu Nina) - Website E Commerce	NEGOTIATION	LOST	Cancel Project, dikerjakan internal	Rp150.000.000,00	2024-06-30	NO TAG	DEL	NaN	...	10.0	update follow up	TASK
Bunda BC - Optimisasi Ads di Marketplace	INITIAL MEETING/CALL	NaN	NaN	NaN	2024-06-30	NO TAG	DEL	Bunda BC	...	25.0	update follow up	TASK
Bank Hana - E procurement	INITIAL MEETING/CALL	LOST	Klien Pindah kerja	Rp5.000.000.000,00	2024-06-30	NO TAG	DEL	Bank Hana	...	17.0	update follow up	TASK

Figure 3. Dataset Collection from Customer History.

3.2. Data Preprocessing

The data preprocessing process is carried out to clean and format the data and adjust the attributes used (such as figure 4) to be suitable for model analysis. These steps include handling missing values, deduplication, and normalizing the data. This preprocessing method is important to improve data quality and ensure that the model can function optimally [19], [20]. Text data is processed using Natural Language Processing (NLP) techniques to break the text into smaller units. In doing text preprocessing, the NLTK library is used by tokenizing to break the text into word units, then stopwords to eliminate common words that do not have a major influence on the overall meaning of the text and applying stemming to change words to basic forms. Next, WordCloud will be used to visualize the words that appear most often in the data (as in table 2). WordCloud provides an overview of the frequency of frequently occurring words and helps identify relevant information that has the potential for further analysis [21].

Deal Name	Label	Type Activity	Note
Translation SM NETA X	DEAL	0	deal harga, dibayar
ERP fase 1	DEAL	0	project sudah selesai , menunggu pembayaran
Pak Ardianta By Ncc -ARDCA MADAM	DEAL	0	Deal cocok untuk MADAM
ERP fase 2	DEAL	0	Deal harga, dibayar
\nAdvanced Training Mazda CX60	DEAL	0	Deal harga, dibayar
...	...	...	...
Sales Training (Volvo Cars)	COLD	TASK	MoM Kris dengan Pak Toto_Volvo Cars Indonesia....
Pembuatan Logo - ERA JAYA	0	TASK	Sudah kirim quotation , sedang di review
Software Seni (Bu Nina) - Website E Commerce	LOST	TASK	Sudah meeting dengan tim , kebutuhan website d...
Bunda BC - Optimisasi Ads di Marketplace	0	TASK	Mau meeting di tanggal 08 Juni 2024 sama mas G...
Bank Hana - E procurement	LOST	TASK	Sudah beberapa kali follow up ke Pak Vincent c...

Figure 4. Attributes Used to Build the Model.

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Table 2. Frequency of Occurring Words.

Cold	Warm	Hot
		

Lost	Deal
	

3.3. Feature Extraction

Feature extraction is an important stage in data processing that affects model performance. In this study, two feature extraction techniques were applied: Term Frequency-Inverse Document Frequency (TF-IDF) and Tokenizer Padding. TF-IDF is used for non-sequential data representation, giving weight to words based on how often they appear in the document and across the corpus (such as Equation 1, Equation 2, and Equation 3). In contrast, Tokenizer Padding is used to convert text data into numerical representations appropriate for deep learning models, thus preserving the order and temporal context of the data [22].

The TF-IDF value of a word t in document d is the result of the multiplication of TF and IDF.

$$\mathrm{TF(t,d)} = \frac{\text{Number of occurences of word t in document d}}{\text{Total number of words in document d}} \tag{1}$$

$$\mathrm{IDF(t,D)} = \log\left(\frac{\mathrm{N}}{\mathrm{df(t)}}\right) \tag{2}$$

$$\mathrm{TF-IDF(\,t,d,D)} = \mathrm{TF(t,d)} \times \mathrm{IDF(t,D)} \tag{3}$$

t is the word (term), and d is the document. Then N is the total number of documents in the corpus. $df(t)$ the number of documents that contain the word t. Log to reduce the weight of very common words.

This equation gives a higher weight to words that often appear in a particular document but rarely appear in other documents, thus prioritizing more significant words for a document in the context of an entire document collection. Furthermore, a padding tokenizer is used to ensure that all text sequences are the same length. This is important because deep learning models, such as LSTM and GRU, require inputs with consistent measurements [19]. Tokenization is the process of converting text into a numeric token, where each word in the text is converted to an integer that corresponds to its index in the vocabulary. Padding, on the other hand, is used to add a zero value (or other value) to a shorter sequence to match the maximum length that has been specified.

3.4. Splitting Data and Build Model

The data were divided into a subset of training and testing to evaluate the model's performance with a ratio of 80:20 [19], [20], [23]. division, carried out using the percentage technique of the target classes in both subsets, is crucial to minimize overfitting and ensure that the model can be accurately measured on data that has never been seen before. This process reassures the accuracy of the model.

Modeling is carried out by implementing several classification algorithms, including Random Forest, Gradient Boosting, AdaBoosting, and Neural Network, as well as deep learning models such as LSTM and GRU. Each model is applied using different feature extraction techniques to evaluate its performance in classifying customers based on their historical interactions.

3.5. Evaluation Model

Model evaluation is carried out by measuring the accuracy, precision, and recall of each model to assess the classification's performance. The evaluation results show a significant difference in performance between the machine learning model and the deep learning model. The evaluation was measured using the confusion matrix technique through Equation 4, Equation 5, and Equation 6.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

True Positive (TP): The amount of positive data that is predicted to be correct. True Negative (TN): The amount of negative data that is predicted to be correct. False Positive (FP): The amount of negative data that is incorrectly predicted as positive (also called a Type I error). False Negative (FN): The amount of positive data that is incorrectly predicted to be negative (also called a Type II error).

4. Results and Discussion

In the current data-driven era, the development of an accurate recommendation model is a key factor in enhancing user interaction. A significant strategy in this endeavor is the utilization of deep learning. Deep learning algorithms offer an alternative to building Customer Relationship Management systems under big data conditions. To achieve effective performance of deep learning models, testing is conducted through performance evaluation, as outlined below.

4.1. Building a Recommendations Model using Deep Learning

In this study, several classification models were tested to build a recommendation system for classifying customers based on their historical interactions. The models used include Random Forests, Gradient Boosting, AdaBoosting, Neural Networks, and deep learning models such as LSTM and GRU. With several treatments, the extraction of the main features is used, namely TF-IDF and tokenizer Padding for Machine Learning models (Random Forest, Gradient Boosting, and AdaBoosting) and deep learning models Neural Networks (LSTM, GRU).

Based on table 3, the test results show that the model with TF-IDF feature extraction achieves the highest accuracy of 82%. Machine learning models that rely on TF-IDF, such as Random Forest, Gradient Boosting, and AdaBoosting, provide competitive and reliable results in classifying customers. However, when using the Tokenizer and Padding features, these machine learning models do not show optimal performance. On the other hand, deep learning models with LSTM and GRU algorithms are superior in using data extracted with Tokenizer and Padding, especially GRU, which achieves the highest accuracy of 88.23%.

Table 3. Results of Evaluation of The Performance of The Classification Model

Algorithms	**Parameters**			
	Feature Extraction	**Accuracy (%)**	**Precision**	**Recall**
Random Forest	TF-IDF	82.00	0.76	0.82
	Tokenizer Padding	71.00	0.85	0.71
Gradient Boosting	TF-IDF	82.00	0.76	0.82
	Tokenizer Padding	59.00	0.71	0.59
AdaBoosting	TF-IDF	82.00	0.79	0.82

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Algorithms	Parameters			
	Feature Extraction	**Accuracy (%)**	**Precision**	**Recall**
	Tokenizer Padding	35.00	0.27	0.35
Neural Network	TF-IDF	82.35	0.74	0.82
	Tokenizer Padding	70.00	0.85	0.71
LSTM	TF-IDF	41.00	0.17	0.41
	Tokenizer Padding	86.47	0.84	0.85
GRU	TF-IDF	41.00	0.17	0.41
	Tokenizer Padding	88.23	0.86	0.87

This difference in performance can be explained through differences in model structure. Machine learning algorithms such as Random Forest and Gradient Boosting are more effective at handling non-sequential data, so feature extraction such as TF-IDF, which focuses on the frequency of words in documents, gives better results. Meanwhile, deep learning models such as LSTM and GRU are designed to handle sequential data by considering the sequence and temporal context of the data. Tokenizers and Padding, which convert text into numerical representations appropriate for deep learning models, provide more relevant sequential information for LSTM and GRU models.

The advantage of GRU over LSTM in this study can be attributed to its ability to handle data sequences more efficiently and with fewer parameters. GRU's simpler structure reduces the likelihood of overfitting the training data, which may occur in more complex LSTM models. With an accuracy of 88.23%, GRU proved superior in classifying customers based on their historical interactions. Moreover, while GRU outperforms LSTM, the interpretability of these deep learning models remains a challenge. Deep learning models are often perceived as "black boxes," making it difficult to explain their predictions in human-understandable terms. This lack of transparency is a critical limitation in CRM applications, where understanding customer behaviour and decision-making is crucial. To address this issue, future work could explore methods to enhance the interpretability of these models. Techniques such as attention mechanisms or Layer-wise Relevance Propagation (LRP) could be applied to provide insights into how different features contribute to the model's predictions.

4.2. Artificial Intelligence Powered Kodein CRM

The AI-powered Customer Relationship Management system developed in this study is designed to improve customer relationship management at Kodegiri company by utilizing artificial intelligence technology. The system integrates deep learning algorithms, specifically GRU, to classify customers into five relevant categories: cold, warm, hot, deal, and lost, as shown in figure 5.

In figure 5, the CRM system has a Deals feature; there is a recommendation module that provides strategic advice for each category of customers. For example, for customers in the 'hot' category, the system recommends a more personalized approach or a special offer to drive conversions. While customers are in the 'cold' category, recommend strategies to increase engagement or specific marketing campaigns. Thus, the overall AI-powered CRM system that was developed provides a powerful tool to improve customer relationship management and maximize sales potential at Kodegiri company. Then, supporting attributes are used to make recommendations in the process through customer activities, as shown in figure 6. In figure 6, customer activity is analyzed based on interactions that occur, such as "New", "Initial Meeting", "Quotation", "Negotiation", "Deal", "Payment", and "Paid".

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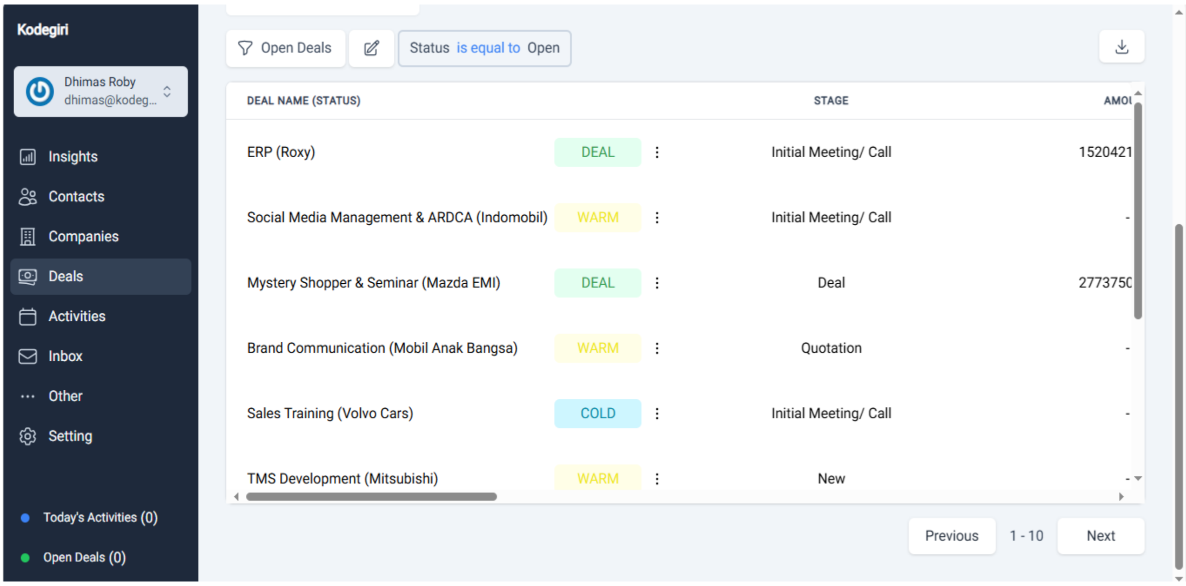

Figure 5. Kodein's CRM Powered by Artificial Intelligence for Level Recommendations.

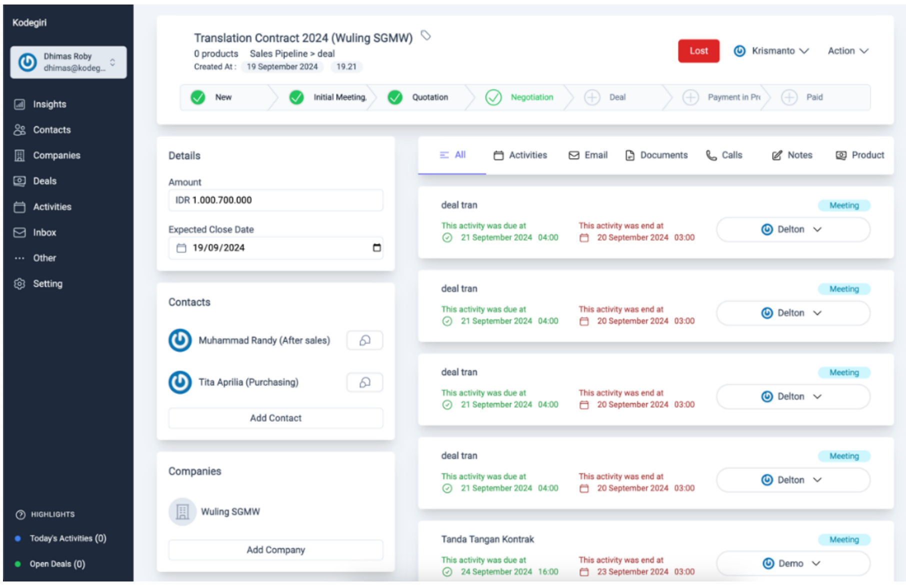

Figure 6. Kodein's CRM on Customer Activity Features.

5. Conclusion

This study demonstrates the profound impact of feature extraction methods and classification models on the performance of CRM recommendation systems. The findings indicate that algorithms like Random Forest, Gradient Boosting, and AdaBoosting are well-suited for non-sequential data with TF-IDF features, while deep learning models such as LSTM and GRU are adept at handling sequential data using Tokenizer and Padding. Notably, GRU, with an accuracy of 88.23%, outperformed LSTMs in managing data sequences, suggesting that the GRU-based deep learning approach holds significant potential in enhancing the personalization level of CRM systems based on customer historical interactions.

6. Declarations

6.1. Author Contributions

Conceptualization: S.S., M.L.L.U., D.A.P., M.A.G., S.V.M.; Methodology: S.S., M.L.L.U. and S.V.M.; Software: S.S., and N.A.R.; Validation: S.S., A.P.W., and A.R.; Formal Analysis: S.S., S.V.M., and B.L.M; Investigation: S.S.;

Resources: M.L.LU., A.P.W., and B.L.M.; Data Curation: D.A.P., and S.V.M.; Writing Original Draft Preparation: S.S; Writing Review and Editing: S.V.M., S.S., M.A.G., and D.A.P.; Visualization: F.K.A., N.A.R., B.L.M., A.P.W and A.R. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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