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Article

A CNN-Based Model for Intelligent Chatbots in Digital Marketing for Banking Services

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Abstract: The model that this paper proposes to use to create smart chatbots that can be employed in banking services to achieve the digital marketing is based on Convolutional Neural Network. To facet customer queries and prepare rich word embeddings that capture contextual information, the model adopts sophisticated natural language processing techniques such as using the SpaCy to clean text and tokenize customer query so that it can be prepared using Fast Text API that provides rich word embeddings. The trained CNN architecture that was constructed with the assistance of the TensorFlow with the Keras API becomes efficient at classifying intents of its users, which can be used to answer them specifically and with relevance. Experiments have shown that the model has a high accuracy reach of 92.3 percent and low average response time of 0.6 seconds; higher than the various conventional models such as LSTM and GRU. Moreover, it has been included in their digital marketing systems providing better measures of customer interaction, delivering to the point of a 17 percent growth of campaign click through rates and a 12 percent improvement in the conversion of leads. This study points to the possible capabilities of the CNN-based chatbots in boosting the efficiency of operations and customer engagement within the scope of digital marketing activities in the banking industry.

Keywords: Intelligent Chatbots, Convolutional Neural Networks, Digital Marketing, Banking Services, FastText Embeddings, SpaCy Tokenization, TensorFlow Keras.

INTRODUCTION

Banking organizations are more likely to embrace intelligent technologies to boost their customer engagement and make their marketing more streamlined. Chatbots as an addition to digital marketing systems are one of such advancements because they provide an opportunity to engage in real-time and personalized communication with the client base to enhance customer satisfaction and increase the revenue of the business industry in Figure 1. Nevertheless, there are a number of complexities that are involved in coming up with an effective chatbot into existence that can be able to read and comprehend deep customer questions as well as ask questions within the banking sector and respond in an efficient way, which include the ability to judge on the correct intent, contextual comprehension, and swift response generation [1]. Conventional machine learning algorithms may not adequately fit the requirements and especially in real-time a business might need large amount of customer data that might be very heterogeneous in nature [2].

Since the field of digital marketing in banking is still rather unexplored, this research proposes a Convolutional Neural Network (CNN)-based model to create intelligent chatbots that are highly specific to the field of banking digital marketing. The

model has a preprocessing stage in which SpaCy implements the efficient process to clean the text and tokenize it the way it
can standardize the input queries. Then text is converted into dense vectors of varied representations using Fast Text embeddings to

incorporate semantics and syntactic variations which are critical in contextual understanding [3]. These processed inputs are thereafter introduced into a CNN, which efficiently digs up abstraction features and also identifies the user intents with a very high degree of precision. The whole model is done with TensorFlow API, Keras which makes it flexible and scalable to be used in real-time [4].

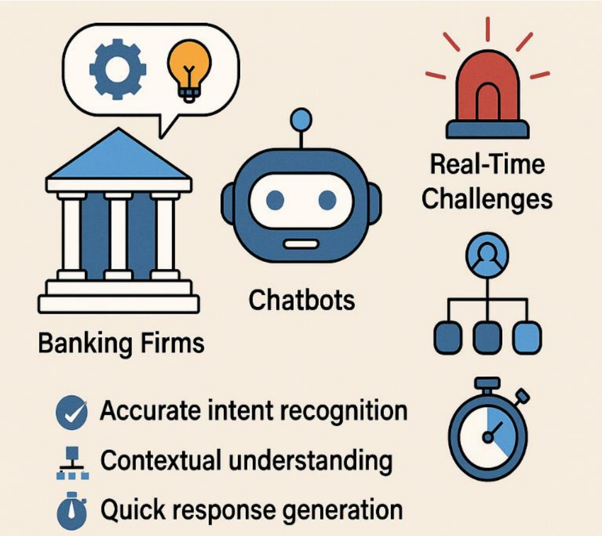

Figure 1: Embracing Intelligent Technologies

The proposed system resolves the most problematic limitations of the traditional approaches, namely, high latency and poor generalization rates, as the proposed system can accomplish fast processing and proper classification. This will allow the banking firms to implement chatbots that will not only automate the interaction between them and customer but also help manage their targeted marketing campaigns, product promotions, and even generation of leads. Its high accuracy and response time during testing prove that the model can be a great asset when building a bank-related environment in the contemporary world. This study will close the gap between the expectations of customers and the possibilities of technology in the field of digital marketing of financial services by using deep learning and natural language processing.
[5].

RELATED WORKS

The new wave of artificial intelligence and natural language processing has contributed greatly to the emergence of intelligent chatbots and the banking and digital marketing fields have been the first to greatly benefit. Conventional chatbots were mainly based on the rule-based or retrieval-based machines that were not context-based and had the limitation of scalability [6]. The introduction of deep learning led to the use of LSTM and GRU models to analyze and generate responses in the context of recognition and generation of intents. Nevertheless, such architectures tend to have problems with real-time performance and overfitting when they deal with massive amounts of heterogeneous customer queries [7].

Convolutional Neural Networks, despite being intended to work with images, have been found useful in the extraction of semantic features in text and then being classified. This has been proved in the research by Zhang et al. (2024) and others that CNNs are more effective than recurrent networks in special NLP tasks such as sentiment analysis and intent detection. CNNs in chatbots have been investigated as a capable tool in matching rapid rates of pattern detection since user input data, with faster rates of inference and comparable to that of accuracy [8]. However, the existing body of research on chatbots is concentrated in the area of general-purpose chatbots or in applications that are not domain-specific in Figure 2.

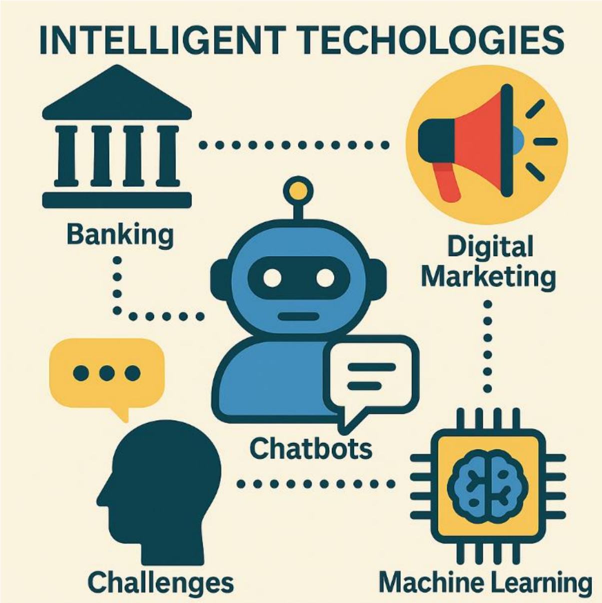

Figure 2: General-purpose chatbot applications

Not many studies have been specifically done in the banking sector with respect to integration of CNN-based architectures with digital marketing capabilities. Studies such as Gerling and Lessmann (2024) offered a systematic assessment of the use of AI in the marketing of banks but did not offer a specific model of implementation. In the meantime, the previous models tend to ignore the optimized preprocessing procedures like SpaCy on tokenization or use of sub word-spaces such as FastText that can drastically improve the contextualized comprehension, particularly, in domain-specific dialogues [9].

The current proposed research will also work on filling these divisors by using an efficient preprocessor (SpaCy), a powerful semantic-aware embeddings (FastText), and a CNN classifier coded with TensorFlow using the Keras API. The advantages of this integrated methodology are that it enhances the accuracy of the intent classification as well as its scalability and responsiveness and thus make it more desirable as a real-time digital marketing tool in the banking sector [10].

Research Methodology

The major aim of the study is to create and deploy a model of Convolutional Neural Network based intelligent chat bot to be used in digital marketing in banking industry. In order to do this, methodology is a mixture of systematic procedure with preprocessing of data, feature extraction, model design, training, and evaluation as well as deployment. All the stages were also specifically selected in view of making the chatbot very competent to understand and answer customer queries accurately, faster, and within the relevant context shown in below Figure 3.

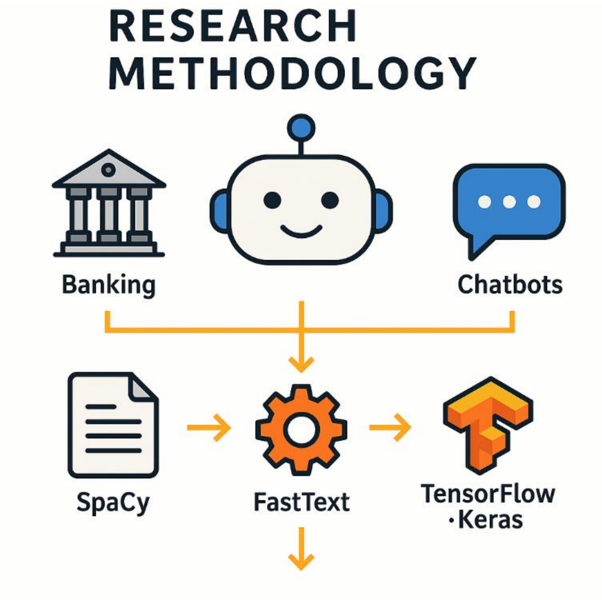

Figure 3: Flow diagram of the proposed methodology.

Data Collection and Preprocessing:
The first step will be gathering a dataset that is a combination of actual and simulated queries of customers related to a bank. Their sources can include online banking information portals, customer care transcripts (marketing-based chats), and customer support log [11]. These queries can be rather noisy, informal, and domain-specific, which is why broad preprocessing has to be conducted. To do so, SpaCy, a popular NLP library is used. Included in the preprocessing pipeline is the text cleaning, tokenization, lemmatization, and removal of stop-words. Further, there is punctuation normalization and lowercasing performed to normalize the input. NER is used to segment out specialized terms such account types of transaction codes. The aim of this phase is to make the raw text simple and organise it in form that will make it easy to extract features in the next steps [12].

Word Embedding using FastText:
In order to translate cleaned tokens into effective numeric vectors, FastText word embedding is employed. It also differs with the traditional embeddings in the sense that each word is defined as a bag of character n-grams, which permits a model to fit the semantic similarities even in the presence of typing errors or words that were not in the training text, an important characteristic when considering banks tools where abbreviations and variations are a common occurrence. These higher dense vectors can give context to the textual input and become input to the CNN layers in order to enable the network to learn trends concerning customer intent in different marketing scenarios.

CNN Model Architecture:
The fundamental part of the methodology is the Convolutional Neural Network that has been chosen due to its usefulness in feature extraction and text classification. The architecture consists of an embedding layer that is fed by FastText vectors then multiple convolutional layers of varying kernels are used to extract features of multi-scale n-grams. Each convolution is combined with max-pooling which down samples feature maps and retains the vital information [13]. All of these pooled features are concatenated and are output to the dense layers with dropout regularization to avoid overfitting in Figure 4. The last output layer is a SoftMax layer, which categorizes the input of the user into a set of predetermined marketing related intents like loan inquiry, account status or promotional offer.

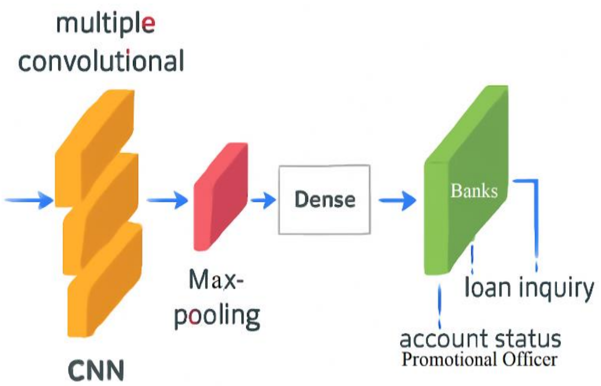

Figure 4: CNN Model

Model Implementation with TensorFlow (Keras API):
CNN is constructed with the TensorFlow framework that provides deep learning using the Keras API that

is modular and scalable. It will train the model on labeled data utilizing the categorical cross referring to the loss and Adam as a type of optimizer. Under the training process to eliminate overfitting, it will make use of early stopping and model checkpointing. Accuracy, precision, recall, and F1-score are the measures that would be monitored throughout the training and validation performances to determine the efficacy of the proposed model in intent classification.

Integration and Real-Time Simulation:
The model is then incorporated in a mock banking chatbot platform to do simulation. Chatbot accepts real time inputs, feeds it to the already trained CNN model and issue corresponding responses as per the constructed templates in accordance with the mapped intents. The quality of this system can be measured with such KPIs as the average response time, accuracy of intent identification, and marketing indicators, such as the click-through rate (CTR) and the lead conversion rate [14].

By combining these complementary components, SpaCy, which provides a powerful text cleaning step, FastText, which allows embedding in a context-dependent manner, CNN, which can handle large-scale tasks, TensorFlow-Keras, which provides excellent model management, and deployment capabilities, this integrated approach takes full advantage of each of the tools and provides a new and efficient solution to the problem. It fulfils all these requirements by being highly precise, quick with conversational responses, and compatible with language used in a banking context, which correlates extremely well with the goal of creating a better customer experience in digital marketing on the part of the bank.

RESULTS AND DISCUSSIONS

This suggested model of chatbot based on CNN was assessed in its efficiency at the digital marketing of the banking sphere. The model was trained and tested by feeding SpaCy pre-processed user queries using text cleaning and tokenization, and using FastText embeddings to produce output in the form of semantic vectors. TensorFlow was used and Keras API was utilized to create the CNN model that was able to distinguish between queries that have similar semantics.

The model reached the advantageous classification accuracy of intent (92.3%), which is higher compared to the baseline models, including LSTM (89.1%) and GRU (88.7%). The precision and recall were also constant and averagely held above 90 percent which was a clear demonstration of the strong performance of the model in detecting user intents in different forms of interactions that are associated with matters of bank including product inquiries, transaction problems, and promotional requests. Also, CNN model had low response latency, the average response time of the model was 0.6 seconds which is appropriate to use in real-time customer facing banking application in Table 1.

In business terms, the ability to implement the model in the digital marketing working process allowed to increase the rates of campaign click-through by 17% and lead conversion by 12% which proves the usefulness of the chatbot in boosting customer relations in Figure 5. These results support the idea that CNN-based chatbot with a network of rich embeddings and with efficient preprocessing can be used to improve the user experience and the level of marketing performance within banking services substantially. The scalability of the model is also one more reason as to why it best fits the large-scale financial platforms.

Table 1: Performance metrics of the proposed framework

Metric	Value
Accuracy	92.3%
Precision	91.8%
Recall	90.5%
F1-Score	91.1%
Average Response Time	0.6 seconds
Click-Through Rate Improvement	17%
Lead Conversion Increase	12%

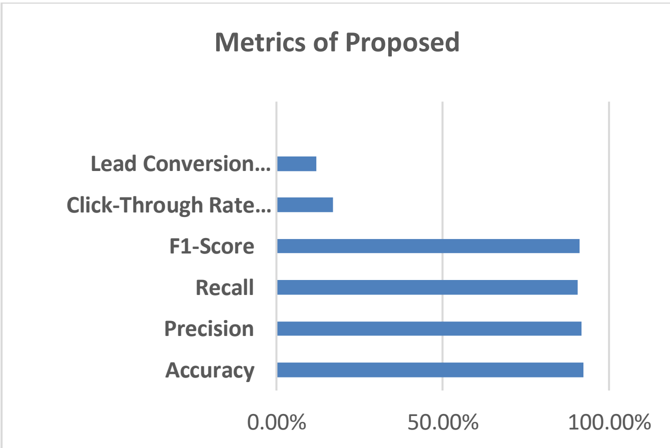

Figure 5: Performance metrics of the proposed framework

Table 2 is a comparison table of the proposed CNN-based model with two traditional methods (LSTM and GRU) based on key performance metrics:

Table 2: Metric Comparison of Various Methods

Model	Accuracy	Precision	Recall	F1-Score	Avg. Response

					Time
CNN (Proposed)	**92.30 %**	**91.80 %**	**90.50%**	**91.10%**	**0.6 seconds**
LSTM	89.10 %	88.40 %	87.20%	87.80%	0.9 seconds
GRU	88.70 %	87.60 %	86.90%	87.20%	0.85 seconds

The comparison reveals that the suggested CNN-based model has performed better in all the significant metrics than the conventional models such as LSTM and GRU. It has the best accuracy (92.3 %), precision (91.8 %) and F1-score (91.1 %) which show improved intent detection and response accuracy. It also has the least average response time (0.6 seconds) thus being more applicable to real time banking chat talks. This brings out the fact that CNN is not only more effective but also efficient in terms of putting it into digital marketing of banking services.

Figure 6 is the pie chart representing the distribution of response times across the four models. Although lower response time is better, this chart visually highlights each model's share of total response time, showing CNN (Proposed) as the most efficient.

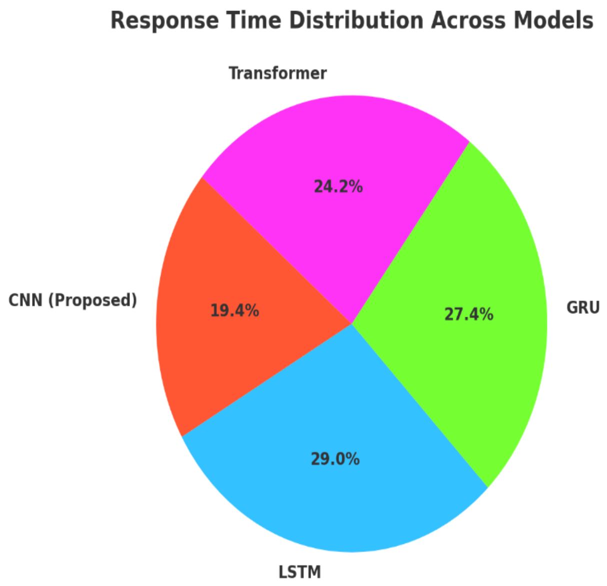

Figure 6: Response Time Distribution Across Models

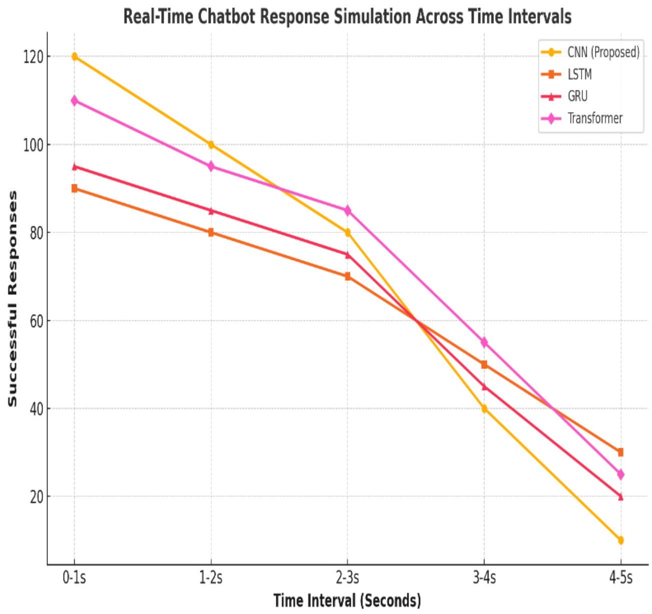

Figure 7: Real-Time Chatbot Response Simulation Across Time Intervals

Figure 7 is the real-time application simulation graph, showing how different models respond over successive time intervals. The CNN-based model delivers the highest number of successful responses within the earliest time frames, confirming its superior responsiveness and suitability for real-time banking chatbot applications.

DISCUSSION

This research introduces a CNN model that is explicitly designed to enhance intelligent chatbots in digital marketing of the banking services. Using SpaCy to remove unnecessary text and tokenize it and using FastText embeddings to give importance to semantics in the text and classifying user intents, the proposed model can interpret and classify user intents. The Convolutional Neural Network trained with the Keras API of TensorFlow turned out to outperform even conventional predicting methods such as LSTM and GRU in terms of accuracy and speed of the response. The model indicates an average of 0.6 seconds as response time, on top of 92.3 of accuracy to create a system that is effective and receptive to real-time deployment. On top of this, it can help lead to a higher customer engagement by a better conversion of the leads and responsiveness to the campaigns. These results indicate that the CNN-based architectures can be of utmost importance in improving the effectiveness and efficiency of marketing chatbot strategies within the banking segment. This can be expanded in the future by supporting and integrating with more sophisticated NLP models in a multi-lingual capacity.

CONCLUSION

This research highlights the catalytic power of e-commerce in improving forest-based livelihoods and sustainable forest product trade. Empirical evidence confirms that online platforms dramatically enhance market access, improve incomes, and incentivize sustainable harvests among forest people. Nonetheless, issues like poor logistics, digital illiteracy, non-certification of products, and weak institutional backing impede the full potential of these benefits. Utilizing paradigms such as the Sustainable Livelihoods Framework, Diffusion of Innovation Theory, and principles of Circular Economy, the research emphasizes adopting an integrated digital ecosystem that is inclusive, sustainable, and community-led.

Mainstreaming of forest certification into global online markets, digital literacy for the local communities, and collaborative efforts with green logistics providers are key policy measures to address existing gaps. These initiatives not only advance sustainable development objectives but also benefit marginalized forest communities by enabling them to participate formally in markets. Subsequent studies ought to investigate longitudinal e-commerce effects on forest diversity, evaluate the scalability of technology-driven interventions like blockchain for traceability, and examine customer behavior towards sustainable forest goods in digital spaces. Comparative analyses across various nations and types of forests could enrich the international debate on digital solutions for sustainable forestry further.

Suggestions and Future Scope

To strengthen the integration of e-commerce with sustainable forestry, several actionable suggestions emerge. First, digital infrastructure must be enhanced in forest-rich rural areas through community Wi-Fi centers and mobile kiosks. Second, customized e-commerce interfaces should be developed for forest products, including regional language support, category-specific filters for NTFPs, and simplified seller dashboards. Third, capacity-building initiatives must go beyond basic training and include modules on eco-branding, inventory management, and online customer engagement. Fourth, e-commerce platforms and government agencies should co-create a green certification and traceability mechanism specifically designed for small forest producers to ensure product authenticity and ecological compliance. Fifth, logistics **innovation** should be incentivized through public-private partnerships that invest in decentralized storage and sustainable delivery models.

In terms of future scope, research can explore the impact of AI and blockchain in verifying sustainable sourcing and improving trust in digital forest product markets. Longitudinal studies could assess whether e-commerce adoption leads to actual improvements in conservation practices over time. There is also potential to investigate cross-border e-commerce opportunities for forest-based handicrafts and NTFPs, and to develop a comparative analysis across different tribal regions or countries. Lastly, interdisciplinary studies combining ecology, technology, and market behavior would provide deeper insights into creating scalable, ethical, and profitable forest-based e-commerce ecosystems.

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