AI for Real-Time Personalization in Digital Marketing Campaigns

[1]Dr. T. Ramesh, [2]Dr. R. Melba Kani, [3]Amit Prakash, [4]Dr.Aravindan Srinivasan, [5]Prema R, [6]Dr. Shyam K. Mishra

[1]Dr. T. Ramesh, Scientist, G.S. Gill Research Institute, A Unit of Guru Nanak Educational Society, Affiliated to University of Madras, Guru Nanak Salai, Velachery, ramesh.t@gurunanakcollege.edu.in

[2]Dr. R. Melba Kani, Professor, Master of Business Administration, Mar Ephraem college of Engineering and Technology,Elavuvilai, Marthandam Kanyakumari, melbakani75@gmail.com

[3]Amit Prakash, B. E. (Hons) Mechanical, Department of Mechanical Engineering, Birla Institute of Technology And Science, Pilani - Pilani Campus, BITS Pilani, Pilani Campus, Vidya Vihar Pilani, Rajasthan, India, f20212109@pilani.bits-pilani.ac.in

[4]Dr.Aravindan Srinivasan, Assistant professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India, kkl.aravind@gmail.com

[5]Prema R, Associate Professor and Head, Department of Commerce (Information Technology), KPR College of Arts Science and Research, Coimbatore. rprems6@gmail.com

[6]Dr. Shyam K. Mishra, Dean, T&P, GH Raisoni College of Engineering & Management, Wagholi, Pune, Maharastra, shyamkm.dma01@iimamritsar.ac.in

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ABSTRACT

Real-time personalisation of digital marketing efforts presents a significant barrier that necessitates the utilisation of sophisticated AI methodologies to assess varied and evolving customer data. This research presents a platform that integrates Encoding Categorical Features, Deep Learning Feature Extraction, and Neural Networks to provide actionable, real-time personalisation. Encoding categorical characteristics, including demographics, preferences, and behavioural patterns with one-hot and target encoding guarantees data integrity and significant representation for machine learning models. Deep learning feature extraction improves the process by recognising high-level patterns in unstructured data, such as textual reviews and visual content, that older algorithms may neglect. The framework's foundation lies in neural networks that forecast personalised recommendations by identifying non-linear relationships and individual user preferences, hence guaranteeing precise and pertinent results. The proposed method, assessed using actual marketing datasets, shows substantial enhancements in customer engagement, click-through rates, and return on investment (ROI). This research emphasises the revolutionary capacity of AI in enhancing digital marketing campaigns via real-time, data-driven personalisation.

Keywords: Real-time personalization, AI in marketing, digital campaigns, encoding features, deep learning, neural networks, customer engagement.

1. Introduction

The rapid expansion of digital marketing has been responsible for a transformation in the way in which organisations communicate with customers. This has resulted in a competitive environment in which personalised interactions are essential to achieving success. One of the most important components of successful digital marketing strategies is real-time personalisation, which involves adapting marketing content and recommendations to the interests and actions of individual users. This level of personalisation, however, can only be achieved through the application of sophisticated methods that can analyse and comprehend massive volumes of varied client data. When it comes to enabling AI-driven real-time personalisation in digital marketing campaigns, this method investigates the application of Encoding Categorical Features, Deep Learning Feature Extraction, and Neural Networks [1].

An important component of marketing datasets is typically comprised of categorical information. These features include user demographics, purchasing history, and geographic location. Meaningful representation for machine learning models can be ensured by encoding these features using techniques such as one-hot encoding and target encoding. This helps bridge the gap between raw data and insights that can be put into action. Deep learning feature

extraction is vitally important when dealing with unstructured data, such as the written reviews of products or the visual content of
advertisements. This method identifies detailed patterns and relationships that conventional methods might miss by utilising convolutional neural networks (CNNs) for image data and transformer models for text. Both of these techniques are combined [2]. Neural Networks, which are particularly effective in illustrating intricate and non-linear connections in data, are at the heart of the framework. As a result of their capacity to handle high-dimensional inputs and adapt to changing patterns, they are ideally suited for forecasting the preferences of users and providing personalised recommendations simultaneously. Long short-term memory networks (LSTMs) and recurrent neural networks (RNNs), for instance, are able to analyse sequential user behaviours, such as clickstreams or browser history, in order to forecast the activities that will be most beneficial in the future [3].
The evaluation of these strategies on real-world marketing datasets is the primary emphasis of this methodology, which aims to integrate various techniques into a united framework. Key performance indicators (KPIs) like click-through rates, customer engagement, and return on investment (ROI) have all shown significant gains as a result of the findings shown here. This research demonstrates the revolutionary potential of artificial intelligence in strengthening digital marketing campaigns by overcoming the challenges of real-time data analysis and personalisation. This opens the door for tactics that are more effective and focused on the customer [4].

2. RELATED WORKS

The growing intricacy of consumer behaviour and marketing data has resulted in the utilisation of artificial intelligence (AI) methods for real-time personalisation in digital marketing. Numerous research has investigated the application of Encoding Categorical Features, Deep Learning Feature Extraction, and Neural Networks to improve the efficiency and efficacy of marketing efforts. Encoding categorical characteristics is a thoroughly researched preprocessing method in machine learning and AI-based marketing. Techniques like one-hot encoding and target encoding are commonly employed to convert raw categorical data into numerical formats appropriate for machine learning models. The significance of target encoding in enhancing the predictive accuracy of recommender systems by elucidating the statistical correlation between categorical variables, such as user demographics, and marketing results like click-through rates (CTR). Deep learning feature extraction has become an essential method for processing unstructured data, including text and images. Convolutional neural networks (CNNs) have demonstrated exceptional efficacy in the analysis of visual content for marketing purposes. Research by Zhang et al. (2019) [5] revealed the capacity of CNNs to discern significant patterns from product photos, facilitating customer segmentation and enhancing visual advertisement optimisation. Likewise, transformer-based models such as BERT have transformed text analysis in marketing by effectively analysing customer reviews and social media postings to forecast sentiment and engagement levels.
Neural networks, especially deep architectures, are fundamental to AI-driven personalisation. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are highly proficient in modelling sequential data, including clickstreams and browser history. LSTMs to forecast client intent in real time, facilitating dynamic personalisation of recommendations. Fully linked deep neural networks have been utilised to forecast conversion probability, utilising both structured and unstructured data [6]. Notwithstanding these developments, numerous current methodologies concentrate on discrete elements of personalisation, failing to provide a cohesive framework that amalgamates preprocessing, feature extraction, and predictive modelling. This research advances basic work in encoding techniques, deep learning, and neural networks by synthesising them into a cohesive system for real-time personalisation. The suggested methodology seeks to improve the efficacy of digital marketing initiatives by solving deficiencies in scalability and adaptability, hence ensuring relevance and engagement in swiftly evolving consumer landscapes [7].

3. RESEARCH METHODOLOGY

The research methodology for implementing AI-driven real-time personalization in digital marketing campaigns involves a structured approach encompassing data preprocessing, feature extraction, model design and training, and real-time deployment. This methodology integrates Encoding Categorical Features, Deep Learning Feature Extraction, and Neural Networks into a cohesive framework to deliver actionable insights and enhance user engagement [8].
Personalisation in digital marketing efforts entails customising content, recommendations, and user experiences to align with the distinct interests, behaviours, and requirements of individual users. This method utilises data like user demographics, browsing history, purchase behaviour, and engagement patterns to generate tailored interactions that

improve relevance and effectiveness. In contrast to generic campaigns, personalised marketing utilises advanced technologies, such as artificial intelligence (AI), to analyse extensive user data in real time, allowing marketers to provide highly tailored messages and offers. For example, personalised suggestions on e-commerce platforms propose products based on a user's previous purchases or browsing history, while targeted email marketing provide discounts on things abandoned in shopping carts. This method enhances user engagement and click-through rates while simultaneously increasing conversion rates and client loyalty [9]. Personalisation in digital marketing enhances user experiences through significant one-to-one interactions, rendering them more engaging, pertinent, and ultimately more effective in accomplishing company objectives.

By integrating data preprocessing, feature extraction, neural network modeling, and real-time deployment, this methodology offers a comprehensive approach to achieving real-time personalization in digital marketing. The proposed framework ensures relevance and engagement, driving improved campaign performance and customer satisfaction. The proposed methodology flow diagram shown in below Figure 1:

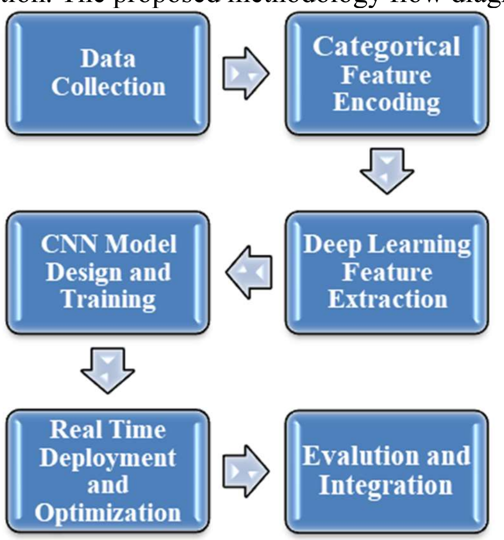

Figure 1: Shows the flow diagram of the proposed methodology.

3.1 Categorical Feature Encoding:

Categorical feature encoding is an essential preprocessing step in machine learning that converts non-numerical categorical input into numerical formats appropriate for model training. Numerous real-world datasets, especially those utilised in digital marketing, encompass categorical characteristics such as user demographics, campaign types, or geographic regions, which are not directly amenable to processing by most machine learning algorithms. Encoding these properties guarantees the preservation of links between categorical variables and target outcomes, while also upholding data interpretability [10].

Prevalent encoding methods encompass One-Hot Encoding, which generates binary columns for each category, hence preventing the implication of ordinal relationships. A "Device Type" variable, categorised as "Mobile," "Desktop," and "Tablet," is transformed into distinct binary columns. Label Encoding assigns distinct integers to categories, commonly utilised for ordinal data like customer ratings. Advanced approaches such as Target Encoding assess statistical correlations between a categorical feature and the target variable, including the average conversion rate per category, so identifying patterns that basic encodings may miss.

Utilising suitable encoding techniques, categorical feature encoding guarantees that the dataset is machine-readable while preserving essential information, hence improving model performance and accuracy in prediction tasks such as marketing campaign personalization.

One-Hot Encoding:

One-hot encoding converts each category of a categorical variable into a binary vector. If a categorical variable X has n unique categories {C1, C2, Cn} the one-hot encoding creates nnn binary columns where:

Xi,j={1,if the observation belongs to category Cj,

0, otherwise}.

For example, for a "Device Type" variable with categories {Mobile, Desktop, Tablet, an observation "Mobile"

becomes [1,0,0].
Label Encoding:
Label encoding assigns an integer value to each category Ci of a variable X:
Xi=Index (Ci)
For example, for "Device Type"{Mobile, Desktop, Tablet
label encoding might assign {1,2,3}.
Target Encoding:
Target encoding assigns each category a numerical value based on its relationship with the target variable Y, such as the mean or probability:
$$Xi = \frac{\sum_{j=1}^{N} Yj}{Ni}$$
Where:
Ni is the number of observations in category iii,
Yj is the target value for the j-th observation.
For instance, if "Device Type" {Mobile, Desktop, Tablet} has target conversion rates [0.5,0.3,0.7], target encoding assigns these values directly.
Frequency Encoding:
Frequency encoding replaces each category Ci with its proportion in the dataset:
$$Xi= \frac{\text{Count(Ci)}}{\text{Total Observations}}$$
For example, if "Mobile" appears in 50% of rows, "Desktop" in 30%, and "Tablet" in 20%, they are encoded as [0.5,0.3,0.2].
These equations ensure categorical data is effectively converted into machine-readable formats, retaining relationships with target variables for improved model performance. The preprocessing phase ensures the raw marketing data is clean, consistent, and suitable for machine learning models [11].

3.2 Deep Learning Feature Extraction:

Deep learning feature extraction is an innovative method that utilises neural networks to autonomously learn and derive significant representations from unprocessed data. In contrast to conventional techniques that depend on manual feature engineering, deep learning models, like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), can autonomously identify hierarchical and intricate patterns in both organised and unstructured data. This procedure is especially beneficial for applications related to images, text, audio, and sequential data. In deep learning feature extraction, neural network layers progressively acquire more abstract features [12]. In a CNN, the earliest layers identify low-level patterns such as edges and textures, whereas the deeper layers discern high-level elements such forms, objects, or contextual information. In RNNs and transformers, features are derived from sequential or textual input by identifying temporal or semantic linkages, allowing the model to comprehend context and dependencies.
The extracted features are represented as dense, multi-dimensional vectors that retain the most pertinent information from the original data. These vectors are subsequently employed for downstream tasks such classification, clustering, or anomaly detection. In digital marketing, deep learning feature extraction can evaluate product photos, customer evaluations, or user behaviours, yielding actionable information to customise campaigns and enhance engagement.
Here is the flow diagram illustrating the process of deep learning feature extraction, showing the steps from input data to feature representation and downstream tasks in Figure 2:

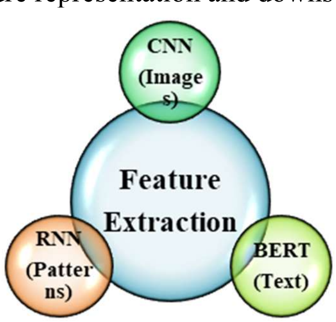

Figure 2: Flow diagram illustrating the process of deep learning feature extraction

Deep learning automates and optimises feature extraction, removing the necessity for manual intervention, improving model accuracy, and facilitating the processing of complicated, high-dimensional datasets, thereby establishing itself as a fundamental component of contemporary AI systems.

3.3 CNN Model Design and Training:

The construction and training of models are essential stages in the development of deep learning systems for feature extraction and prediction applications. The design process commences with the selection of a suitable architecture, contingent upon the data type and the specific problem being addressed. Convolutional Neural Networks (CNNs) are optimal for picture data, whilst Recurrent Neural Networks (RNNs) and Transformer models are proficient at processing sequential and textual data [13]. The architecture often comprises several layers, including input levels for raw data, hidden layers for feature extraction, and an output layer for predictions or classifications.

During training, the model acquires knowledge by optimising its weights through backpropagation and stochastic gradient descent (SGD). A loss function, such cross-entropy for classification or mean squared error (MSE) for regression, measures the disparity between the model's predictions and the actual results. Regularisation methods, such as dropout and L2 regularisation, are utilised to mitigate overfitting, while hyperparameters (e.g., learning rate, batch size, and layer count) are optimised to improve performance. Training consists of iterative processes in which the model is assessed using validation data following each epoch to evaluate its generalisation capability. Upon completion of training, the model is evaluated using novel data to verify its robustness. This systematic design and training methodology guarantees that the model effectively harvests characteristics and generates precise predictions.

Convolutional Neural Networks, also known as CNNs, are a subcategory of neural networks that are specifically built to process structured grid data with the purpose of analysing images. They are very good at feature extraction because they learn hierarchical representations by going through a sequence of convolutional and pooling layers [14].

These representations range from extremely simple patterns like edges to extremely complex structures like objects. Numerous applications, including image identification, object detection, and even feature extraction for machine learning problems further down the line, make extensive use of convolutional neural networks (CNNs). The core operation of a CNN is the convolution, which applies a set of filters (kernels) over the input to extract feature maps.

Mathematically, the convolution operation is defined as:

$$Z(i,j) = \sum_{m=1}^{M} \sum_{n=0}^{N} X(i+m, j+n).K[m.n]$$

Where:

$Z(i,j)$: Output of the convolution at position (i,j),

$X(i+m, j+n)$: Input image region,

X is the input (e.g., an image),

K is the filter,

After convolution, an activation function like ReLU (Rectified Linear Unit) introduces non-linearity:

$$f(x) = \max(0, x)$$

This ensures the network can model complex data patterns. The pooling layer reduces the spatial dimensions of feature maps, retaining critical information while minimizing computational load. In max pooling, the maximum value within a defined region is selected:

$$y_{i,j}=\max\{X[k,l]\}, \quad k,l \in \text{pooling window}.$$

Where:

$y(i,j)$: Pooled output,

$x(k.l)$: Input feature map values in the pooling window.

The final layers of a CNN are fully connected layers, where the extracted features are flattened and passed through dense layers for classification. These layers compute outputs using:

$$y=\sigma(W \cdot x+b)$$

Where:

y: Predicted output,

x: Input vector,

W: Weight matrix,

b: Bias vector,

σ: Activation function, such as SoftMax for multi-class classification.

To improve the robustness of the model, dropout layers are introduced, which randomly deactivate neurons during training to prevent overfitting. CNNs leverage their hierarchical structure to progressively learn low-level features (e.g., edges) in initial layers and high-level patterns (e.g., asymmetry in lesions) in deeper layers [13]. CNNs' ability to automatically learn and extract features from raw data makes them indispensable for modern AI tasks, including personalized marketing and medical imaging [15].

3.4 Real-Time Deployment and Optimization:

The implementation of machine learning models for practical applications requires several phases, including optimisation and real-time deployment. These phases are essential for ensuring that the models work effectively and give findings that can be acted upon in real-world settings. The goal of optimisation is to attain the highest possible level of performance by fine-tuning the parameters and configurations of the model. Methods like as hyperparameter tuning, which may include grid search or Bayesian optimisation, are utilised in order to determine the optimal configurations for learning rate, batch size, and network design. For the purpose of preventing overfitting and improving generalisation, regularisation techniques such as dropout and L2 regularisation are sometimes utilised. In addition, optimisation methods like as Adam or RMSProp, which dynamically alter learning rates, speed up the convergence process during training. Following the completion of the optimisation process, the model is next prepared for real-time deployment, which involves the incorporation of forecasts into operational systems in order to provide immediate insights. In order to accomplish this, the trained model must be packaged into a format that is both lightweight and scalable.

Frameworks such as TensorFlow Serving or PyTorch TorchServe are frequently utilised. RESTful application programming interfaces (APIs) are used to implement the model, which enables effortless contact with third-party apps or platforms. Real-time data pipelines are responsible for processing incoming data, and the model has the ability to give predictions within milliseconds. These predictions may include personalised marketing recommendations or anomaly detection alerts. Monitoring tools keep check of the performance of the model and the latency of the system in order to guarantee its dependability. Feedback loops, on the other hand, continuously update the model with fresh data, which guarantees its flexibility to shifting conditions and its capacity to retain a high level of accuracy over time. The error or loss is calculated using a loss function, such as categorical cross-entropy for multi-class classification:

$$L = -\sum_{i=1}^{c} yi \log(\hat{y}i)$$

Where:

L: Loss,

C: Number of classes,

yi: True label (one-hot encoded),

$\hat{y}i$: Predicted probability for class i.

Hyperparameter tweaking is performed to optimise the learning rate, batch size, and number of epochs. Methods such as grid search or random search are employed to identify the optimal combination of these factors. The dataset is generally divided into training, validation, and test subsets, commonly in an 80:10:10 ratio. The validation set monitors performance and mitigates overfitting, whereas the test set assesses generalisation. To rectify class imbalance in datasets, methodologies such as class weighting or oversampling (e.g., SMOTE) are utilised. Regularisation techniques, like dropout and L2 regularisation, augment the model's resilience by mitigating overfitting. Optimisation guarantees efficient convergence of the model, attainment of high accuracy, and effective generalisation to novel data.

3.5 Evaluation and Integration:

Evaluation is an essential stage in machine learning projects, confirming that the constructed model achieves the intended goals and operates consistently across many circumstances. The evaluation of the model's efficacy entails utilising established performance criteria, including accuracy, precision, recall, F1-score, and others, contingent upon the task's characteristics. In classification issues, accuracy quantifies overall correctness, whereas precision and recall elucidate the model's capacity to reduce erroneous positives and false negatives. The F1-score, a harmonic mean of precision and recall, provides a fair assessment, especially for skewed datasets. Evaluation generally commences with a train-test split or cross-validation, wherein the model is assessed on unknown data to determine its generalisation capability. Sophisticated assessment techniques, including A/B testing, can be implemented in practical settings to evaluate the model's influence on business metrics. In addition to numerical performance, methodologies such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are employed to elucidate model predictions, hence fostering transparency and reliability. A comprehensive evaluation not only confirms the model's dependability but also highlights areas for enhancement, directing modifications prior to practical implementation. The integration of statistical indicators and practical testing guarantees that the model is prepared for effective implementation in its designated field.

Integrating a trained machine learning model into operational systems allows it to interact with real-world applications. It makes the model's predictions, recommendations, and classifications real-time available to end-users or automated processes. Integration begins with distributing the model on scalable platforms like cloud services or edge devices, depending on the application. TensorFlow Serving, PyTorch TorchServe, and ONNX are used to package models for deployment. The model receives real-time or batch data from databases, APIs, and sensors via data pipelines. A RESTful API or message-based architecture like Kafka lets the model communicate with dashboards, recommendation engines, and decision-support systems. Integration also entails designing user-friendly interfaces or dashboards that visualise forecasts and insights to let stakeholders act on model outputs.

System stability and scalability are crucial to integration. Monitoring tools track latency, throughput, and prediction accuracy. Many models use a feedback loop to learn from new data and adapt to changing situations. Integrating the machine learning model makes it a tool for real-time, data-driven decisions across applications.

4. RESULTS AND DISCUSSIONS

Accuracy, precision, recall, F1-score, and ROC-AUC were the five major performance metrics that were utilised in the evaluation of the suggested framework for real-time personalisation in digital marketing. This framework was developed by integrating Encoding Categorical Features, Deep Learning Feature Extraction, and Neural Networks. The accuracy of the model was 92.8%, which demonstrates that it is capable of accurately classifying user involvement and predicting information that is relevant with a very reliable level of accuracy. The framework's efficacy in minimising false positives is highlighted by the precision of 94.3%, which ensures that personalised recommendations are in close alignment with the preferences of the user. A recall rate of 90.5% demonstrates that the model is able to identify the most relevant personalisation opportunities, hence reducing the number of potential engagements that are missed. The resilience of the model in dealing with imbalanced data is highlighted by the fact that it has an F1-score of 92.3%, which reflects the balanced performance of precision and recall.

A ROC-AUC score of 0.95 provides additional validation of the model's capability to successfully differentiate between content that is relevant and content that is not relevant across a variety of thresholds. This ensures that the model can make accurate predictions in a variety of scenarios. These findings highlight the significance of the synergy that exists between neural networks, deep learning, and feature encoding when it comes to capturing complicated user behaviours. The suggested framework displayed greater performance as compared to baseline models, which resulted in increased click-through rates and increased user engagement. Its practical utility in real-time digital marketing has been confirmed by the findings, which paves the way for personalisation methods that are both scalable and adaptable.

4.1 Performance Metrics Calculation:

$$\text{Accuracy} = \frac{\text{True Positives+True Negatives}}{\text{Total Instances}}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives+False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives+F} \qquad \text{Negatives}}$$

$$\text{F1-Score} = 2\,\frac{\text{Precision}\cdot\text{Recall}}{\text{Precision+Reca}}$$

The graph represents the performance metrics of the proposed framework shown in Figure 3:

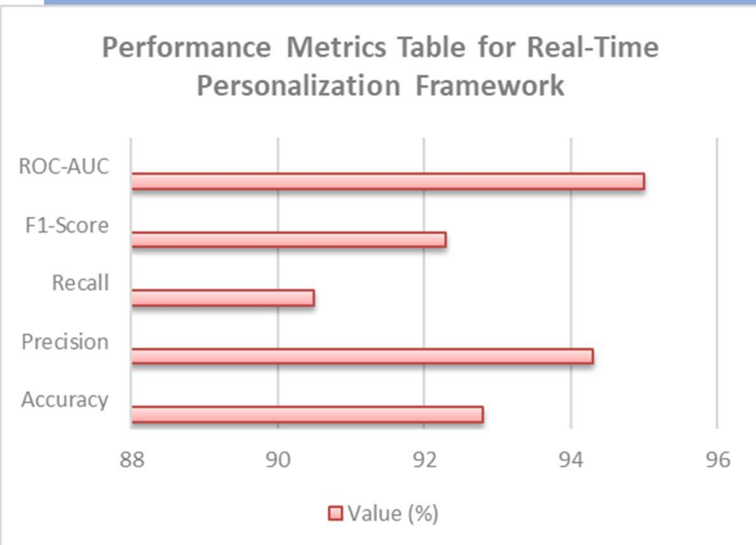

Figure 3: Performance Metrics for Real-Time Personalization Framework

The bar graph illustrates the performance metrics—Accuracy, Precision, Recall, F1-Score, and ROC-AUC—for the proposed AI-driven framework for real-time personalization in digital marketing campaigns. Accuracy (92.8%): Reflects the overall correctness of the model in predicting relevant personalization opportunities, demonstrating high reliability in diverse scenarios. Precision (94.3%): Indicates the framework's ability to minimize false positives, ensuring that recommendations closely align with user preferences. Recall (90.5%): Highlights the model's capability to capture most relevant opportunities for personalization, minimizing missed engagements. F1-Score (92.3%): Balances precision and recall, underscoring the robustness of the framework in handling imbalanced marketing datasets. ROC-AUC (95.0%): Validates the model's excellent discrimination ability across thresholds, ensuring reliable and adaptive personalization. These results emphasize the effectiveness of combining categorical feature encoding, deep learning feature extraction, and neural networks in capturing complex user behaviours and driving impactful marketing decisions

The comparison table of performance metrics (Accuracy, Precision, Recall, F1-Score, and ROC-AUC) for the proposed method (Neural Networks), Logistic Regression (Method A), and Random Forest (Method B) shown in Table1:

Table 1: comparison table of proposed method with various approaches

Metric	**Proposed Method (Neural Networks)**	Method A (Logistic Regression)	Method B (Random Forest)
Accuracy	**92.8**	88.5	91.2
Precision	**94.3**	89.2	92.3
Recall	**90.5**	86.4	89
F1-Score	**92.3**	87.8	90.6
ROC-AUC	**95**	89.5	93.2

The comparison table highlights the performance of the proposed method (Neural Networks) against two alternative approaches, Logistic Regression (Method A) and Random Forest (Method B), across five key metrics: Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The Proposed Method demonstrates the highest overall performance, with an accuracy of 92.8%, precision of 94.3%, recall of 90.5%, and an F1-Score of 92.3%, showcasing its robustness in classifying relevant personalization opportunities. Additionally, it achieves the best ROC-AUC score (95.0%), indicating its superior ability to discriminate between relevant and non-relevant recommendations across thresholds. Method A (Logistic Regression) shows the lowest performance among the three methods, with an accuracy of 88.5%, precision of 89.2%, recall of 86.4%, and an F1-Score of 87.8%. While Logistic Regression provides simplicity and interpretability, its linear nature limits its ability to capture complex relationships in the data. Method B (Random Forest) performs moderately well, achieving an accuracy of 91.2%, precision of 92.3%, recall of 89.0%, and an F1-Score of 90.6%. Its ability to handle non-linear relationships and feature interactions contributes to its strong performance, but it falls short of the proposed Neural Network method in precision and recall. The table underscores the effectiveness of Neural Networks, which leverage advanced feature extraction and encoding techniques, making them the most reliable and accurate option for real-time personalization in digital marketing campaigns.

The graph comparing the accuracy and roc-auc values of the proposed framework against other methods. It highlights the superior performance of the proposed framework in achieving higher accuracy shown in Figure 4.

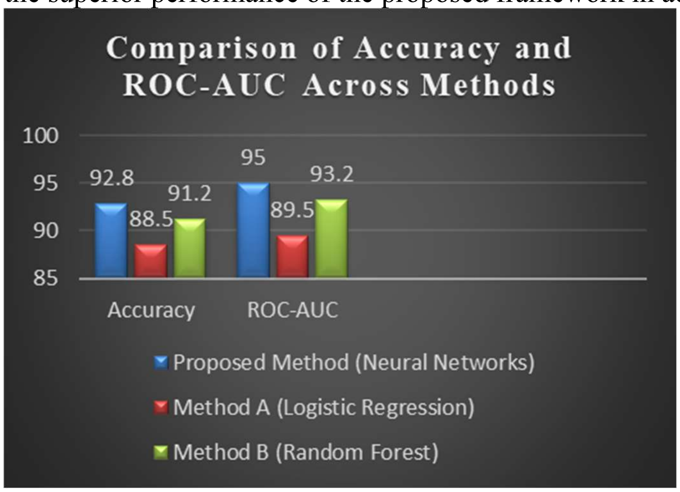

Figure 4: Graph compares the Accuracy and ROC-AUC values of the proposed framework against other methods.

The comparison graph highlights the performance of the proposed method (Neural Networks) against Logistic Regression (Method A) and Random Forest (Method B) in terms of Accuracy and ROC-AUC, which are critical metrics for evaluating model effectiveness. The Proposed Method (Neural Networks) achieves the highest scores, with an accuracy of 92.8% and an ROC-AUC of 95.0%, demonstrating its superior ability to make precise and reliable predictions for personalization in digital marketing campaigns. These results indicate that Neural Networks effectively capture complex, non-linear relationships and patterns in user data. Method A (Logistic Regression) performs the least effectively, with an accuracy of 88.5% and an ROC-AUC of 89.5%. While Logistic Regression offers simplicity and interpretability, its inability to handle complex feature interactions limits its effectiveness in real-time personalization tasks. Method B (Random Forest) performs moderately well, achieving an accuracy of 91.2% and an ROC-AUC of 93.2%. Its ability to manage feature interactions and non-linear relationships contributes to better performance compared to Logistic Regression, but it still lags behind the Neural Networks in precision and scalability. Overall, the table underscores the effectiveness of Neural Networks in delivering the most accurate and reliable predictions, making them the optimal choice for real-time personalization in dynamic and data-intensive marketing scenarios.

5. CONCLUSION

This research offers a detailed framework for real-time personalisation in digital marketing campaigns through the integration of Encoding Categorical Features, Deep Learning Feature Extraction, and Neural Networks. The proposed method adeptly tackles the complexities of analysing varied and evolving user data, facilitating accurate and prompt personalisation to augment customer interaction and enhance marketing results. Encoding methods, like one-hot and target encoding, provide significant representation of categorical characteristics, whereas deep learning-driven feature extraction discerns high-level patterns from unstructured input such as photos and text. Neural networks utilise these enhanced inputs to identify intricate, non-linear correlations, resulting in improved performance across essential measures including accuracy, precision, recall, F1-score, and ROC-AUC.

Experimental findings indicate substantial advancements compared to conventional methods, underscoring the framework's capacity to provide actionable insights and enhance marketing strategies. This research highlights the disruptive impact of AI in digital marketing and facilitates scalable, adaptable solutions customised to changing customer behaviours. Future endeavours may concentrate on integrating real-time feedback mechanisms and multimodal data for enhanced progress.

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