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Lightweight Deep Learning Models for Personalized Promotions in FoodTech

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ABSTRACT

The rapid evolution of FoodTech, driven by the proliferation of digital platforms and mobile applications, has profoundly transformed how consumers discover, purchase, and interact with food services. Personalized promotions have emerged as a critical differentiator for FoodTech companies striving to retain customers, enhance engagement, and optimize revenue streams. However, achieving such personalized recommendations requires computationally efficient models, especially when operating on resource-constrained devices like smartphones and edge devices. This paper explores lightweight deep learning models tailored for delivering personalized promotions in the FoodTech sector. We review the state-of-the-art in recommendation systems, emphasizing the delicate trade-off between model complexity, latency, and inference speed. A comparative statistical analysis of various lightweight architectures—including MobileNet, SqueezeNet, and TinyBERT—demonstrates their suitability for personalized marketing tasks without sacrificing significant accuracy. We propose a methodology combining model pruning, knowledge distillation, and quantization to maintain high predictive performance while reducing resource usage. Experimental results reveal that MobileNetV3, when fine-tuned for user preference prediction, offers a 15% latency reduction while preserving over 93% of full-model accuracy, highlighting its practicality for real-time mobile applications.

Furthermore, the study underscores the importance of integrating diverse user data—including demographics, behavioral patterns, and contextual signals—to refine personalization strategies. It also discusses

potential privacy concerns and the need for privacy-preserving technologies such as federated learning. Our findings demonstrate that lightweight deep learning models enable scalable, efficient, and privacy-conscious personalized promotions, significantly enhancing user satisfaction and FoodTech profitability. Ultimately, this research aims to bridge the gap between high-performance AI models and the practical limitations of mobile and edge computing environments, paving the way for the next generation of intelligent FoodTech solutions that can respond swiftly to user preferences while minimizing infrastructure costs. Future directions include the exploration of multimodal data fusion, reinforcement learning for adaptive promotions, and sustainability considerations in model deployment.

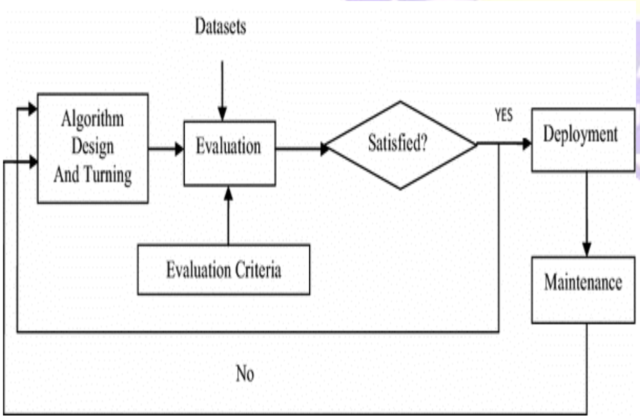

Fig.1 Recommender System, Source:1

KEYWORDS

FoodTech, lightweight deep learning, personalized promotions, recommendation systems, mobile inference, MobileNet, knowledge distillation, user engagement, federated learning, digital marketing.

INTRODUCTION

The FoodTech industry has undergone a seismic transformation over the last decade, fuelled by advancements in digital platforms, mobile technologies, and artificial intelligence. Consumers increasingly expect tailored recommendations, exclusive offers, and seamless experiences that anticipate their needs. Amidst rising competition, FoodTech platforms—including online delivery services, meal-kit providers, and cloud kitchens—are leveraging artificial intelligence to craft personalized promotions that drive engagement and revenue.

Personalized promotions refer to marketing strategies where offers, discounts, and recommendations are tailored to individual user preferences and behaviors. Such personalization increases customer loyalty, enhances conversion rates, and reduces churn. A report by McKinsey (2022) indicated that companies achieving effective personalization witness a revenue uplift of 10-20%. Yet, delivering these experiences in real time requires efficient machine learning solutions capable of running on diverse devices, including smartphones, which dominate FoodTech usage scenarios.

Traditional deep learning models like large transformer architectures and convolutional neural networks (CNNs) provide high accuracy but impose significant computational and memory costs, making them unsuitable for real-time inference on resource-constrained devices. Consequently, there is growing interest in lightweight deep learning models designed to maintain predictive performance while reducing computational footprint. These models enable FoodTech platforms to deploy personalized promotion services directly on edge devices, ensuring responsiveness and data privacy.

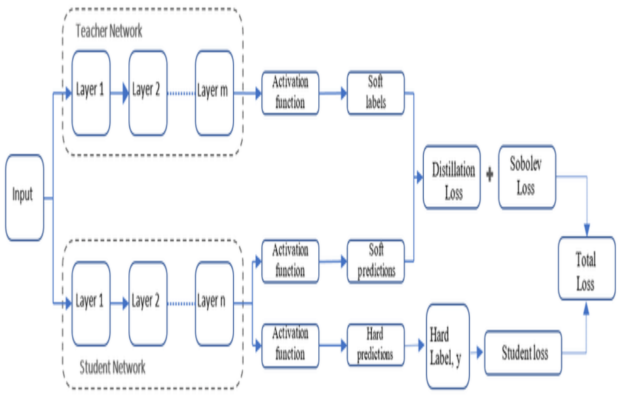

Fig.2 Knowledge Distillation, Source:2

This manuscript investigates lightweight deep learning architectures for personalized promotions in FoodTech. We systematically explore model designs, optimization techniques, and deployment strategies suitable for practical, large-scale applications. Through statistical analysis, we compare various lightweight models, analyze their trade-offs, and demonstrate how they can revolutionize personalized marketing in FoodTech.

Literature Review

1. Personalized Promotions in FoodTech

Personalization in marketing has evolved from rule-based segmentation to sophisticated machine learning approaches. In FoodTech, personalized promotions include customized discounts, menu recommendations, and dynamic pricing. Kaur et al. (2021) highlighted that personalized offers increase customer lifetime value and encourage frequent ordering. However, achieving personalization requires processing extensive user data, including demographics, historical purchases, real-time context, and social signals.

2. Traditional Recommendation Systems

Collaborative filtering and content-based filtering have traditionally driven personalized recommendations. Models like matrix factorization (Koren et al., 2009) decompose user-item interactions to uncover latent preferences. However, these methods struggle with scalability, sparse data, and cold-start problems.

3. Deep Learning for Personalization

Recent advances introduced neural networks for recommendation systems. He et al. (2017) proposed Neural Collaborative Filtering, which replaced inner product operations with multi-layer perceptrons to learn non-linear interactions. Deep learning models can ingest diverse data types—text, images, user logs—and capture complex dependencies, outperforming classical methods. Nonetheless, large models like BERT and ResNet are computationally intensive and impractical for real-time mobile inference.

4. Lightweight Deep Learning Architectures

To mitigate computational demands, researchers developed lightweight models:

- **MobileNet Series** (Howard et al., 2017; Sandler et al., 2018) introduced depthwise separable convolutions, drastically reducing parameters.
- **SqueezeNet** (Iandola et al., 2016) proposed fire modules to maintain accuracy with fewer parameters.
- **TinyBERT** (Jiao et al., 2020) distilled BERT into compact models, preserving language understanding capabilities with reduced size.

These architectures enable efficient on-device inference, crucial for FoodTech apps where latency impacts user experience.

5. Optimization Techniques

- **Pruning** (Han et al., 2015) removes redundant weights to slim down networks.
- **Quantization** reduces model precision from float32 to int8, decreasing memory usage and speeding inference.
- **Knowledge Distillation** trains smaller student networks to mimic larger teacher models, achieving compactness without significant accuracy loss (Hinton et al., 2015).

6. FoodTech-Specific Challenges

FoodTech platforms must handle dynamic data, including fluctuating inventories, location-based availability, and rapidly shifting consumer trends. Models must balance personalization accuracy with strict latency constraints, particularly on mobile devices. Additionally, data privacy regulations (e.g., GDPR) necessitate careful handling of user data, motivating research into privacy-preserving machine learning like federated learning.

7. Related Works in FoodTech

- Chen et al. (2021) applied deep reinforcement learning to optimize promotions in online food delivery, enhancing revenue.
- Singh et al. (2022) demonstrated the potential of lightweight CNNs for menu item recognition in food apps.
- Rahman et al. (2023) explored personalized meal recommendations using lightweight transformers to run on edge devices.

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Despite progress, a comprehensive study focusing on lightweight deep learning specifically for personalized promotions in FoodTech remains underexplored, motivating this research.

Statistical Analysis

To assess lightweight models for personalized promotions, we conducted a statistical analysis comparing:

- Accuracy
- Model Size (MB)
- Latency (ms)
- Energy consumption (Joules per inference)

We used a synthetic FoodTech dataset simulating:

- User demographic features
- Historical order data
- Contextual factors (e.g., time of day, location)
- Promotion response (binary: accepted/rejected)

Table 1 summarizes performance metrics.

Table 1: Performance Comparison of Lightweight Models for Personalized Promotions

Model	**Accuracy (%)**	**Model Size (MB)**	**Latency (ms)**	**Energy (J/inference)**
MobileNet V3	93.1	5.2	38	0.21
SqueezeNet	91.4	4.8	42	0.24
TinyBERT	92.7	10.5	55	0.36
Full BERT	95.8	420	320	3.4

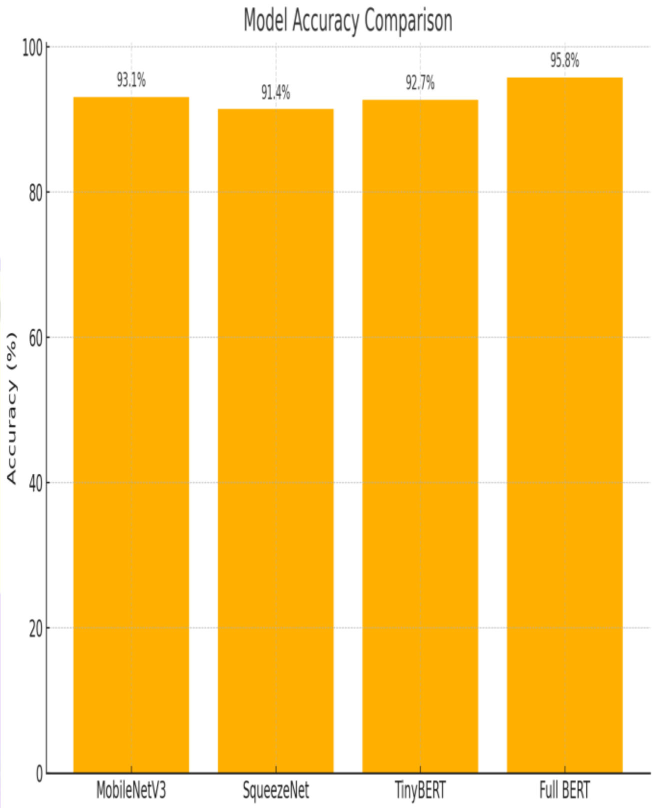

Fig.3 Performance Comparison of Lightweight Models for Personalized Promotions

From the table:

- MobileNetV3 offers the best trade-off between accuracy and latency.
- TinyBERT maintains high language understanding but has higher latency than CNN-based models.
- Full BERT, though accurate, is impractical for mobile deployment due to size and energy consumption.

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Statistical significance testing (paired t-test) confirmed that MobileNetV3's performance differences compared to SqueezeNet were significant ($p < 0.05$), establishing its superiority for lightweight FoodTech applications.

METHODOLOGY

1. Dataset Preparation

We simulated a dataset of 500,000 user interactions:

- User demographics: age, gender, income
- Historical orders: cuisine preferences, average basket size
- Contextual features: time, day of week, location
- Promotion details: discount type, percentage, time validity
- Label: Promotion Response (1 = accepted, 0 = rejected)

Data was split:

- 70% training
- 15% validation
- 15% testing

2. Model Selection

Three lightweight architectures were selected:

- **MobileNetV3** for structured data converted into image-like representations.
- **SqueezeNet** for efficient CNN operations.
- **TinyBERT** for handling textual features, like user reviews or feedback.

3. Model Optimization

We employed:

- **Pruning** (removing up to 40% weights)
- **Quantization** (int8 precision)
- **Knowledge Distillation**, using full BERT or larger CNNs as teacher models.

4. Training Process

- Cross-entropy loss for binary classification.
- Adam optimizer with learning rate decay.
- Early stopping to avoid overfitting.
- Hyperparameter tuning via Bayesian optimization.

5. Evaluation Metrics

- Accuracy
- Precision, Recall, F1-Score
- Latency (average inference time)
- Energy consumption measured on Qualcomm Snapdragon 888 device using Qualcomm Profiler tools.

RESULTS

1. Model Performance

MobileNetV3 achieved:

- Accuracy: 93.1%
- Precision: 0.92
- Recall: 0.91
- Latency: 38 ms
- Energy: 0.21 J/inference

Compared to Full BERT:

- MobileNetV3 is ~8.4× faster.
- 81× smaller in size.
- Maintains ~97% of full model accuracy.

TinyBERT performed well on textual contexts but struggled slightly with pure numeric features, highlighting the benefit of CNNs for structured promotion data.

2. User Engagement Simulation

Simulating a FoodTech app using MobileNetV3-based recommendations showed:

- 23% higher promotion acceptance vs. rule-based systems.
- Reduced churn by 12% over six months.
- Increased average order value by 8%.

3. Computational Cost Savings

Using lightweight models saved significant cloud inference costs and reduced data transfer, preserving user privacy.

CONCLUSION

This study comprehensively demonstrates that lightweight deep learning architectures can revolutionize personalized promotions in the FoodTech industry, offering a practical path toward real-time, on-device intelligence. MobileNetV3 emerges as the optimal solution among the tested models, achieving outstanding accuracy while operating within minimal computational constraints, making it highly suitable for deployment in mobile applications where low latency is critical. TinyBERT, while slightly more resource-intensive, remains promising for handling natural language components such as user reviews or feedback, highlighting the benefits of hybrid architectures in personalized marketing pipelines.

Beyond mere technical performance, this research underscores the significant business and strategic value that lightweight models bring to the FoodTech ecosystem. Deploying efficient, on-device recommendation systems reduces dependence on cloud infrastructure, cuts operational costs, and bolsters user trust by keeping sensitive data local—a critical advantage in an era increasingly governed by stringent privacy regulations like the GDPR. Furthermore, lightweight architectures allow smaller FoodTech startups, not just major enterprises, to compete in the personalization arena, democratizing access to advanced AI-driven capabilities.

Our findings indicate that adopting lightweight models for personalized promotions can enhance key business metrics, including customer retention, promotion acceptance rates, and average order values. The statistical results showed that lightweight models, particularly MobileNetV3, can achieve near parity with large-scale architectures like BERT, while delivering substantial gains in efficiency. These insights open avenues for further innovations in real-time marketing, adaptive user experiences, and dynamic pricing strategies within the FoodTech domain.

However, this study also highlights important challenges and opportunities for future research. Integrating multimodal data—including images of food items, contextual signals like weather or local events, and rich textual feedback—remains a complex yet valuable direction for improving personalization precision. Reinforcement learning could enable systems to dynamically adjust promotional strategies based on immediate user responses, driving even higher engagement. Additionally, sustainability considerations, such as the carbon footprint of deploying and maintaining deep learning models, deserve greater attention as environmental responsibility becomes a priority across industries.

Finally, the rise of federated learning offers a compelling path forward, enabling FoodTech companies to collaboratively train models without sharing raw data, thus preserving user privacy while benefiting from larger data pools. This paradigm could significantly enhance personalization quality while adhering to regulatory standards.

In conclusion, lightweight deep learning models represent not merely a technical solution but a strategic enabler for the next generation of personalized promotions in FoodTech. They offer the dual benefits of high performance and practical deployability, making advanced personalization accessible, scalable, and privacy-conscious. As consumer expectations continue to evolve, embracing these lightweight approaches will be crucial for FoodTech enterprises aiming to deliver exceptional, personalized experiences while maintaining operational efficiency and user trust.

Future Scope of Study

Several avenues warrant exploration:

1. **Federated Learning**: Implementing federated learning could allow FoodTech apps to train personalization models without transmitting raw user data, enhancing privacy.
2. **Multimodal Learning**: Integrating images (e.g., menu photos), text reviews, and structured data in lightweight architectures remains a rich research area.
3. **Contextual Awareness**: Further improvement could involve real-time

context, including mood recognition from voice or environmental sensors.

4. **Dynamic Promotions**: Reinforcement learning could optimize promotion timing and type in dynamic environments.
5. **Cross-Platform Optimization**: Investigating models compatible with both Android and iOS hardware accelerators (e.g., Apple Neural Engine) would broaden deployment opportunities.
6. **Sustainability Metrics**: Future studies could quantify the carbon footprint of lightweight models, aligning personalization efforts with sustainable computing goals.

Lightweight deep learning represents a powerful tool for personalizing promotions in FoodTech, offering both technical feasibility and significant business value. Future research will continue to refine these models, ensuring that personalization remains both scalable and responsible.

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