HCLNet: A Hybrid CNN-LSTM Model for Enhanced Healthcare Product Classification for Recommendation

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ABSTRACT

The rapid growth of healthcare commodities requires automated categorization. Effective categorization solutions save time and money and can provide precise recommendations. Poorly annotated data, inconsistency of product category, and imbalanced datasets impede machine learning algorithms in current systems. CNNs work well with large datasets but struggle with the classification of healthcare products due to class imbalance and lack of labeled data. This study presents a Hybrid CNN-LSTM (HCLNet) model to improve the classification of healthcare products and resolve these issues. This method enhances classification using CNN feature extraction and LSTM sequential pattern recognition. HCLNet can better handle class imbalance and limited labeled data with a comprehensive data preprocessing pipeline, including selection, transformation, and filtering. The hybrid design overcomes CNN constraints and captures product feature temporal connections using LSTM layers. HCLNet was compared with ResNet, GoogleNet, and AlexNet, surpassing them. HCLNet classified complex and imbalanced datasets with 96.25% accuracy, 96.60% precision, and 96.05% recall. The proposed method can improve the classification of healthcare products to obtain accurate automated product recommendations.

Keywords-healthcare product classification; CNN-LSTM hybrid model; feature extraction; ResNet-50; GoogleNet; AlexNet

I. INTRODUCTION

Healthcare product classification enhances service and efficiency [1], as it can properly categorize millions of items in massive catalogs updated with new goods from different merchants. As manual product classification is inefficient and error-prone, machine-learning approaches are superior [2]. Text-based classification algorithms suffer from little annotated data, inconsistent classifications, and imbalanced datasets [3]. Product names and descriptions alone can be inaccurate since product images and other information are needed for classification [4].

CNNs have difficulties in healthcare product categorization, especially with insufficient data or unbalanced datasets. Some techniques use computer vision but have limited accuracy, long training times, and expensive computational requirements [5]. To address these issues, this study presents HCLNet, a hybrid architecture that combines CNN models such as AlexNet [6], GoogleNet [7], and ResNet-50 [8] with LSTM [9]. As shown in Figure 1, the proposed system addresses spatial and temporal dependencies using data preprocessing, feature extraction using pre-trained CNNs, and sequence learning using LSTM. Transfer learning uses pre-trained models to reduce training time and improve performance with limited data [10].

CNNs, RNNs, and transfer learning have improved healthcare product classification performance in complex datasets. These methods have low classification accuracy and generalizability due to imbalanced datasets, minimal labeled data, and poor sequence learning. The HCLNet model is a hybrid architecture to address these problems and improve healthcare product categorization. The healthcare dataset is preprocessed for analysis using a feature matrix and data normalization to provide data uniformity and quality for effective training. A new hybrid design combines CNN models (AlexNet, GoogleNet, and ResNet-50) with LSTM networks. CNNs extract complicated spatial aspects of healthcare items, whereas LSTMs learn temporal relationships to improve sequence identification and classification. After splitting the data into training and test sets, the hybrid LSTM generates sequences, and model training using optimization and loss functions fine-tunes the model.

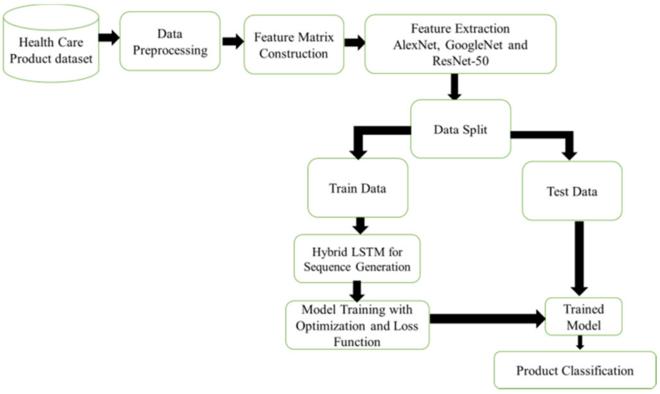

Fig. 1. Proposed HCLNet.

The performance of the HCLNet model was evaluated using specific metrics, showing that it outperformed individual CNN architectures in classification accuracy, precision, and recall. The HCLNet model handled a complicated dataset with classification accuracy of 96.26%, precision of 96.60%, recall of 96.05%, and F1-score of 96.32%, indicating its durability and flexibility. Even with difficult, skewed datasets, the model can automate healthcare product categorization and improve recommendation accuracy.

II. RELATED WORKS

In [11], the Genetic Standard Additive Model (GSAM) was proposed, using a standard model and an evolutionary algorithm to handle uncertainty-related computing challenges. GSAM learning involves startup, evolution, and optimization. This model used unsupervised learning and optimized evolutionary rules. GSAM learning extracts discriminative features from high-dimensional datasets. Wavelet sets can be reduced to achieve this with minimal computational characteristics. In [12], a fuzzy-based decision tree genomic expression data classification method was proposed and compared with a standard decision tree. E-commerce can automate decision-making based on past purchases using Deep Learning (DL). In [13], a lightweight dense-layer DL architecture model was trained using public datasets and achieved great performance. In [14], a multigranular language representation model was proposed. Data were presented using morphological labeling instead of numbers, allowing manual data recovery. In [15], deep autoencoders and belief networks were used to classify healthcare commodities by title and description. This model was GPU-trained on 150 M pictures at five hierarchy levels, achieving 81% accuracy. In [16], BoW and SVM were used for text-based classification. The AlexNet architecture [6] has been applied in almost all fields, including product classification. AlexNet has been compared to superior classification models such as Google Net [7] and ResNet [8]. In [17], visuals outperformed words in product classification. After applying logistic regression for supervised learning, a Confusion Driven Probabilistic Function (CDPF) was proposed to identify the most confusing classes, and the model was individually trained in underperforming regions. In [18], an automated product image categorization method was proposed using a deep CNN. After receiving the feature map, KNN was employed to locate cluster-related commodities. In [19], a CNN-based product categorization and recommendation system was proposed. In [20], a CNN transfer learning image classification system was proposed. This study compared Inception-v3 accuracy with ordinary neural networks. Complex healthcare product classification requires more than text-based and CNN-only methods, especially with little labeled data. CNNs excel at spatial feature extraction but not temporal learning, whereas transfer learning overcomes data scarcity. These issues inspired HCLNet to collect spatial and temporal information using CNN and LSTM for greater classification accuracy and efficiency.

III. PROPOSED SYSTEM

The proposed method applies a preprocessed and well-defined dataset to healthcare product classification. HCLNet is a hybrid architecture that employs several components since healthcare product categorization is difficult. The product dataset is cleaned and standardized before feature matrix development. Feature-extraction models, such as AlexNet, GoogleNet, and ResNet-50, were used to extract features. Separate training and test sets were fed into a hybrid LSTM model for sequence construction and temporal feature learning to enhance model performance. The results showed that hyperparameter tuning significantly improved the design and classification performance of HCLNet. HCLNet achieved a higher accuracy of 96.25%, compared to ResNet-50 (95.37%), GoogleNet (94.82%), and AlexNet (94.38%). Its accuracy, recall, and F1 score make the model a solid automated healthcare product classification solution. HCLNet is a cutting-edge healthcare product classification and recommendation model that uses CNNs and LSTMs for feature extraction and sequence learning.

A. Preprocessing

Several steps were applied to clean and normalize the product dataset. The dataset included healthcare products organized into multiple categories, and consistency was ensured by addressing discrepancies in category labels and grouping similar products. Missing data, particularly in fields such as product descriptions, prices, and ratings, were handled through imputation techniques, where mean imputation was used for numerical fields and mode imputation for categorical ones. For data normalization, min-max scaling was applied to ensure that all features fell within a standardized range, facilitating better model training. The preprocessing steps ensured that the dataset was clean, consistent, and suitable to be fed into the HCLNet model. Preprocessing transforms the raw feature vector x_i into a cleaned and normalized form x_i':

$$x_i' = normalize\ (x_i) \tag{1}$$

This ensures that all features lie within a common range, facilitating better learning in later stages.

B. Feature Matrix Construction

A feature matrix was constructed for each product's features, such as category, price, and ratings, which were transformed into a structured feature vector. These vectors were then compiled into a feature matrix where each row represented a product and the columns represented the normalized feature attributes. Feature extraction was performed using pre-trained CNN models such as AlexNet, GoogleNet, and ResNet-50, which generated high-dimensional feature maps for each product. These feature maps were combined into a comprehensive matrix for further processing. Regarding data augmentation, data transformations focused on data normalization (min-max scaling) and the creation of synthetic examples in some cases to address class imbalances, ensuring the feature matrix was optimized for training the model. The preprocessed data x_i' was converted into a feature matrix F as:

$$F = [f(x_1'), f(x_2'), f(x_3'), \dots.. f(x_n') \quad (2)$$

where $f(x_i')$ represents the feature vector of the i^{th} product. This matrix $F \in R^{n\times d}$ was input to the subsequent feature extraction step.

C. Feature Extraction Using CNN

Feature extraction is performed using pre-trained CNN models (AlexNet, GoogleNet, ResNet-50) to obtain high-dimensional, informative representations. The input data, shaped into a 2D tensor, is first processed through multiple layers of pre-trained CNNs (AlexNet, GoogleNet, and ResNet-50) for feature extraction. The output feature map $\phi CNN(x_i')$ for each product x_i' is computed by passing it through one of these CNN models.

For ResNet-50:

$$\phi ResNet50\ (x_i') = ResNet - 50(x_i') \quad (3)$$

For AlexNet:

$$\phi AlexNet\ (x_i') = AlexNet(x_i') \quad (4)$$

For GoogleNet:

$$\phi GoogleNet(x_i') = GoogleNet(x_i') \quad (5)$$

where $\phi CNN(x_i')$ is the output feature map after convolution. Each CNN model extracts different high-dimensional representations, which are combined to form a comprehensive feature matrix. These feature vectors can be used individually for further processing:

$$\Phi(F) = [\phi AlexNet(F), \phi GoogleNet(F), \phi ResNet50(F)] \quad (6)$$

Following the convolutional layer, a max-pooling operation is applied to down-sample the feature maps and reduce the spatial dimensions:

$$y_{pool} = MaxPooling(\phi CNN\ (x_i')) \quad (7)$$

The pooled features are then flattened into a one-dimensional vector:

$$y_{dense_{cnn}} = ReLU(W_{dense\_cnn} * y_{pool} + b_{dense\_cnn}) \quad (8)$$

D. LSTM for Sequence Generation

In the second branch, the feature matrix $\phi train$ is fed into an LSTM network to capture sequential dependencies between the product features over time. The LSTM operates at each time step t updating its hidden state h_t , which encodes information about the sequence.

The three primary gates that make up an LSTM cell are the input (i_t), forget (f_t), and output (o_t) gates. To maintain and update its cell state (C_t) throughout time, the cell relies on these gates to regulate the flow of information through it. An LSTM cell is controlled by the following equations:

Forget Gate:

$$f_t = \sigma(W_f . [h_{t-1}, x_t] + b_f) \quad (9)$$

where σ the sigmoid activation, W_f is the forget gate weight matrix, and b_f is the bias.

Input gate:

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \quad (10)$$

Cell State Update:

$$C_t = tanh(W_C . [h_{t-1}, x_t] + b_C) \quad (11)$$

The final cell state is updated as:

$$C_t = f_t * C_{t-1} + i_t * \bar{C}_t \quad (12)$$

Output Gate:

$$O_t = \sigma(W_O . [h_{t-1}, x_t] + b_O) \quad (13)$$

The new hidden state h_t is:

$$h_t = O_t * \tanh(C_t) \quad (14)$$

The combined output of the CNN and LSTM branches is fed into a fully connected layer, where the final classification decision is made. The model is trained using cross-entropy loss to classify healthcare products into appropriate categories.

E. HCLNet Proposed Model Architecture

Figure 2 shows the proposed HCLNet architecture, demonstrating the step-by-step process from raw healthcare product data to final product classification. HCLNet combines CNN and LSTM for enhanced healthcare product classification. The CNN component, using the AlexNet, GoogleNet, or ResNet-50 pre-trained models, extracts high-dimensional spatial features from product data. These feature maps are then processed by the LSTM, which learns sequential dependencies, capturing trends such as user interactions or product evolution. The combined CNN-LSTM output is passed through fully connected layers for classification, enabling HCLNet to effectively handle both static and temporal data for improved accuracy on complex healthcare datasets. The max-pooling layer reduces dimensionality and highlights key patterns in these characteristics. When learning long-term data patterns, the LSTM branch captures sequential dependencies in product characteristics using its memory units. The CNN and LSTM branches merge into a fully connected layer to classify spatial and sequential information. The model uses dropout to reduce overfitting and improve generalizability. Finally, a softmax function in the classification layer predicts each healthcare product's class, ensuring a reliable classification system.

The hybrid CNN-LSTM architecture of HCLNet is designed to leverage the strengths of both CNN and LSTM for enhanced healthcare product classification. The CNN component is responsible for extracting high-dimensional spatial features from product data, such as images or structured product attributes. Pre-trained CNN models like AlexNet, GoogleNet, and ResNet-50 are used for this task, generating feature maps that capture intricate patterns in the data. These feature maps are then fed into the LSTM component, which focuses on learning sequential dependencies in the data. The LSTM processes these feature maps over time, capturing temporal relationships and trends, such as patterns in user interactions or product evolution. The combined output of the CNN's spatial feature extraction and LSTM's sequence learning is then passed through fully connected layers for classification. This interaction allows HCLNet to effectively handle both static and temporal information, improving classification accuracy and performance on complex healthcare datasets.

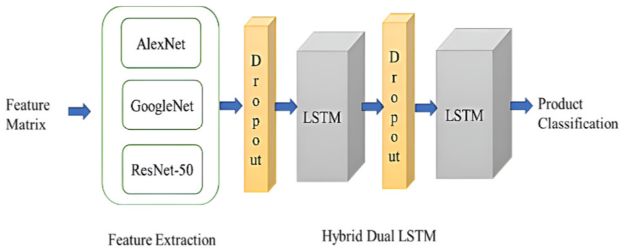

Fig. 2. Architecture of the proposed model.

IV. RESULT AND ANALYSIS

This study examined how LSTM affects CNN design. Google Net, Alex Net, and ResNet-50 are advanced CNNs. Transfer learning is used to shallowly learn each architecture's core properties using healthcare datasets. In the hyperparameter tuning process for HCLNet, this study experimented with different batch sizes, learning rates, dropout rates, and the choice of the optimizer to achieve optimal model performance. The Stochastic Gradient Descent (SGD) was used as the optimizer because of its ability to provide better generalization when trained over several epochs. The learning rate was tuned by testing values between 0.001 and 0.00001, with 0.0001 being selected as the most effective, ensuring gradual convergence without large fluctuations. Batch sizes of 16, 32, and 64 were tested, finding that 16 offered the best trade-off between computational efficiency and convergence stability. The dropout rate was set at 0.5 to prevent overfitting, ensuring that the model retained robustness during training. These hyperparameters were optimized based on their impact on performance metrics such as accuracy, precision, recall, and validation loss, leading to improved model generalization and enhanced classification results on the dataset.

A. Dataset

This study used the Amazon Products 2023 dataset [21]. The dataset contains product names, categories, descriptions, prices, reviews, ratings, and image URLs of almost 1.4 million products and 233.1 million user-generated evaluations, including ratings, price, and sales data until September 2023. These data are used to classify users' purchase history and browsing behavior to suggest health-related products. Although the dataset includes image URLs, this study focuses on structured data, such as product descriptions and user reviews, which is crucial for product classification and recommendation tasks. This dataset provides a comprehensive platform for evaluating the performance of HCLNet in healthcare product classification.

B. Performance Evaluation

Accuracy, recall, precision, and F1-score were used to evaluate the proposed model, as they provide a complete picture of the model's utility [22]. A model's accuracy indicates how well it fits the data. The ability of the model to accurately detect real positives is called recall. Reducing the occurrence of false positives is the primary goal of precision. The F1-score balances recall and accuracy. Taken as a whole, these metrics shed light on the model's strengths and weaknesses over a wide range of scenarios.

$$\text{Accuracy} = \frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{TN}+\text{FP}+\text{FN})} \tag{15}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{16}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TN}+\text{FP})} \tag{17}$$

$$\text{F1}-\text{score} = \frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision}+\text{Recall})} \tag{18}$$

where TP denotes True Positives, TN denotes True Negatives, FP denotes False Positives, and FN denotes False Negatives.

C. Product Classification

Figure 3 shows the AlexNet-LSTM model's training and validation accuracy and loss across 30 epochs on the dataset. The model rapidly improves training accuracy during the first few epochs, stabilizing around 89-91% for validation and training accuracy. Close congruence of training and validation accuracy curves implies the model generalizes effectively to validation data. Training and validation loss decrease steadily to near-zero levels at training's completion with minor fluctuations. This shows that the AlexNet-LSTM model learns dataset patterns without overfitting. Early stopping was used to stop training when the validation loss stopped improving. These adjustments helped stabilize validation loss and improve model generalization on the dataset. Figure 4 shows the GoogleNet-LSTM model's training, validation, and loss across 30 epochs on the healthcare dataset. Model training and validation accuracy increased to 90-92% at the end of training. Training accuracy increased dramatically in the early epochs before stabilizing. Training loss was substantially reduced after 25 epochs. The validation loss varied greatly, indicating mild overfitting. Despite these oscillations, the GoogleNet-LSTM model classified products with high accuracy and modest validation loss, indicating its resilience. Figure 5 shows the accuracy and loss of the ResNet-50-LSTM training and validation over 30 epochs. The model increased training and validation accuracy, stabilizing at 92-94% after training. This model learned product data patterns using ResNet-50 for feature extraction and LSTM for sequence learning. A constant decline in training and validation loss can be observed with occasional deviations, indicating a slight overfitting tendency but effectively regulated. ResNet-50-LSTM's high classification accuracy and low loss make it suitable for healthcare product classification.

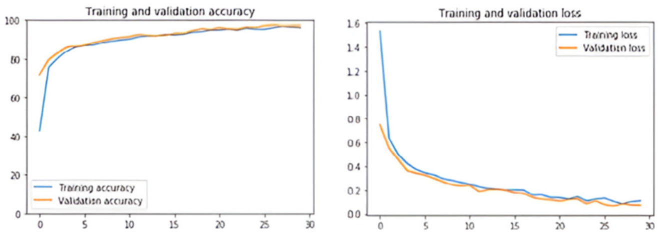

Fig. 3. AlexNet-LSTM model performance.

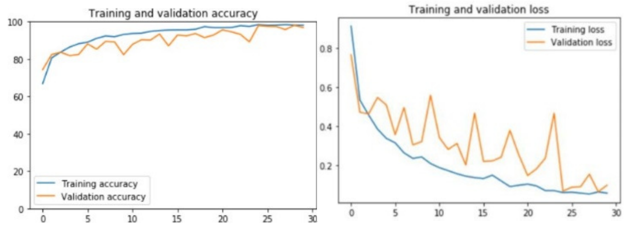

Fig. 4. GoogleNet-LSTM model performance.

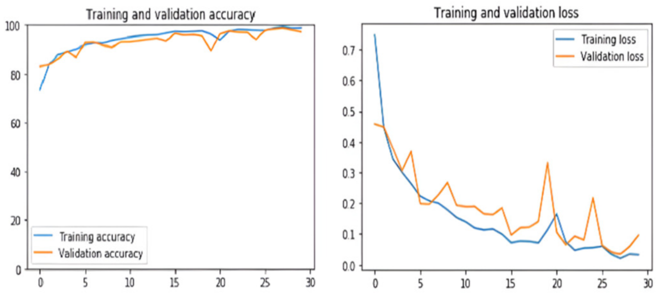

Fig. 5. ResNet50-LSTM model performance.

TABLE I. CLASSIFICATION PERFORMANCE

Model	Accuracy	Sensitivity	Specificity	Precision	F-score
AlexNet-LSTM	94.38	87.69	98.12	92.29	88.94
GoogleNet-LSTM	94.82	90.16	98.91	93.26	91.05
ResNet-50-LSTM	95.37	92.22	99.58	94.71	92.86
HCLNet (combined features)	96.26	96.05	96.5	96.60	96.32

Table I compares the classification performance of HCLNet and other benchmark models on the dataset. The HCLNet model, which incorporates features from several architectures, performs best across all measures, with 96.26% accuracy, 96.05% sensitivity, 96.5% specificity, 96.60% precision, and 96.32% F-score. This is much better than CNN-LSTM models such as ResNet-50-LSTM (95.37%) and GoogleNet-LSTM (94.82%). The HCLNet addresses key challenges in healthcare product classification, such as class imbalance, limited labeled data, and the inability of prior models to capture both spatial and sequential dependencies. Unlike CNN-based models such as ResNet, GoogleNet, and AlexNet that focus only on spatial features, HCLNet integrates CNN for spatial feature extraction with LSTM for sequential pattern learning. This hybrid approach captures both static and temporal relationships, improving classification performance. Through robust preprocessing and transfer learning, HCLNet outperforms previous models in accuracy, precision, recall, and F1-score, making it well-suited for imbalanced healthcare datasets.

D. Discussion

The results show that the HCLNet model had the highest accuracy (96.26%) among the other CNN-LSTM models. Multiple feature extraction methods help HCLNet balance accuracy (96.60%) with recall (96.05%), resulting in a high F-score (96.32%). Although ResNet50-LSTM and GoogleNet-LSTM also perform well, HCLNet's ability to combine features from diverse architectures improves its classification accuracy, making it a reliable healthcare product classification solution.

Experimenting with hyperparameters provided insights into how batch size, learning rate, dropout rate, and optimizer choice affected model performance. A smaller batch size of 16 led to more stable learning, while a learning rate of 0.0001 offered the best convergence. A dropout rate of 0.5 effectively reduced overfitting and using SGD as the optimizer improved generalization, especially with imbalanced data. Fine-tuning these parameters by tracking validation loss and accuracy helped the model achieve optimal classification accuracy, precision, recall, and F1-score. HCLNet includes annotations to highlight key features and patterns. The model focuses on product classification, offering insight into its decision-making process. By zooming in on regions with high variance in validation loss, challenging cases can be identified to improve generalization. These steps enhance both the interpretability and the transparency of the model.

The HCLNet model demonstrates strong potential for generalization to other healthcare datasets and even other product categories due to its hybrid CNN-LSTM architecture, which is designed to handle both spatial and temporal feature extraction. The model's ability to learn from diverse data, such as images and sequential patterns, makes it adaptable to different healthcare products and categories. Although the experiments focused on a specific dataset, the use of pre-trained CNN models such as ResNet-50, GoogleNet, and AlexNet suggests that HCLNet could perform well on other datasets by leveraging its capacity to capture high-level features from new domains with minimal retraining.

HCLNet can be applied in real-time healthcare product classification by leveraging its CNN-LSTM architecture to quickly analyze spatial and temporal features for personalized recommendations. However, scaling for real-time applications poses challenges such as computational complexity and high latency. Optimizing inference through model compression, distributed computing, and handling class imbalance is crucial. Efficient data pipelines and robust infrastructure are also needed to manage large datasets and ensure scalability in real-time applications.

V. CONCLUSION

The proposed HCLNet model demonstrates significant improvements in the classification of healthcare products, outperforming individual traditional CNN-based models such as ResNet, GoogleNet, and AlexNet. With a classification accuracy of 96.25%, a precision of 96.60%, and a recall of 96.05%, HCLNet effectively addresses challenges related to class imbalance and limited labeled data by integrating CNN's feature extraction capabilities with LSTM's sequential learning. This hybrid architecture is highly effective for healthcare product recommendations, offering robust performance and high reliability. This approach allows HCLNet to better handle class imbalance and insufficient labeled data, which are common issues in healthcare datasets. Furthermore, the model's ability to integrate pre-trained CNNs, such as AlexNet, GoogleNet, and ResNet-50, with LSTM for temporal learning is a key innovation that enhances classification performance.

The HCLNet model can be further improved by incorporating attention mechanisms to better capture relevant features and dependencies in healthcare product data, thus improving both classification accuracy and interpretability. Additionally, the HCLNet can be extended to real-time recommendation systems, allowing immediate and context-aware suggestions to users. Future studies should explore sophisticated optimization techniques, such as adaptive gradient methods and advanced regularization, to boost model performance, scalability, and efficiency, especially for large and imbalanced datasets. These improvements can make HCLNet more robust and applicable to real-world healthcare recommendation platforms.

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