Advancing Pneumonia Classification and Detection: Comparative Analysis of Deep Learning Models Using Convolutional Neural Networks

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***Abstract*— Pneumonia is a fatal disease that arises from a bacterial infection in the lungs. If it is not detected in an early stage, it can cause death among young children. Early detection of this disease can play an important role in the effectiveness of the treatment process. The diagnosis is usually monitored from chest X-ray images by an expert radiologist. Due to a lack of confidence in the diagnosis process regarding ambiguous X-ray images or being mistaken for other medical diseases, the application of computer vision is needed to assist radiologists in the decision-making process. In this study, we utilized techniques from transfer learning alongside three architectures based on convolutional neural networks (CNNs) to facilitate the detection of pneumonia and improve the interpretability of diagnostic outcomes. To achieve this, we used a publicly available dataset of 5,863 grayscale chest X-ray images. These images include standard anterior-posterior (AP) and lateral views obtained from unique patients from Guangzhou Women and Children's Medical Center in China (1,583 normal and 4,280 pneumonia images). Before the training, validation, and testing phases, data preprocessing techniques including image resizing and data augmentation were used to prepare the dataset for binary classification. To enhance the generalizability and efficacy of our findings, we utilized high-performing pre-trained models such as DenseNet121, DenseNet169, and ResNet101, evaluating the performance of each architecture against an external validation, and test set. The evaluation results of deep learning models for binary classification of pneumonia demonstrated that DenseNet121 outperformed its counterparts achieving the highest validation accuracy of 98.68% and the lowest loss value of 0.04.**

***Index Terms*— Classification, Pneumonia, Deep learning, Detection, Transfer learning**

I. Introduction and Related Work

Pneumonia, an infection inflaming the air sacs in one or both lungs, impacts millions of people worldwide unnecessarily each year. People with acute pneumonia often experience a combination of symptoms, including a cough that may produce phlegm or be dry, pain in the chest, fever, and breathing difficulty. The severity of the symptoms is widely different from person to person [1]. Pneumonia is responsible for approximately 1.9 million fatalities worldwide annually [2], underscoring its significant impact on global health. This disease notably stands as a predominant health challenge among children, exceeding any other pediatric disease in its toll on individual health, societal well-being, and the strain it places on healthcare systems [3]. Pneumonia involves infectious inflammation of the lung tissue caused by a range of pathogens including bacteria, viruses, fungi, and parasites [4]. Treatment for pneumonia includes the use of antibiotics to combat bacterial forms, antivirals for viral causes, and antifungal agents for fungal infections. Additionally, supportive measures such as adequate rest, maintaining hydration, and managing fever play a crucial role in recovery [5]. However, early detection and appropriate treatment are key to preventing severe complications and death from pneumonia [6].

Early detection of pneumonia from chest X-ray images causes a significant challenge for radiologists. The recognized issue of diagnosing pneumonia stems from the complexity and variability in interpreting chest X-rays, although chest X-ray imaging stands as the most recognized and widely used clinical approach for the detection of pneumonia [7], [8]. Research indicates that applying computer vision techniques on chest X-ray images can assist radiologists in their decision-making process and address these challenges encountered [9]. Algorithms based on Convolutional Neural Networks (CNN) are prominently used in deep learning for analyzing images, especially in the medical field to facilitate the early detection of diseases [10]. In this study, we develop a variety of well-performed Transfer Learning Classifiers (TLC) for early detection of pneumonia using chest X-ray images. This method helps to enhance the diagnostic process, offering radiologists and patients more timely and effective treatment options.

In a study by Kania [11] a novel approach using the VGG16 [12] model for categorization enhanced with genetic algorithms for hyperparameter optimization in binary classification of normal and pneumonia images. Furthermore, Deep Convolutional Generative Adversarial Networks (DCGANs) [13] were implemented to expand the size of a dataset with synthetic pneumonia X-ray images. The dataset utilized to train, test, and validate the deep learning models was gathered from a healthcare institution in Guangzhou, specializing in services for women and children, the same dataset that was employed in our study. The results demonstrate that VGG16 received an 89.50% accuracy and an 87.50% fitness score. After optimization and augmentation with DCGANs, the accuracy increased to 95.50%, and the F1-Score boosted to 94.75%. While genetic algorithms fine-tuned the model's settings for better classification performance, DCGANs augmented the dataset, improving the model's precision in detecting and classifying pneumonia.

Mudasir et al. [14] employed six deep learning models, including CNN, InceptionResNetV2, Xception, VGG16, ResNet50, and EfficientNetV2L for their effectiveness in binary classification tasks differentiating with pneumonia and normal classes. The dataset employed in their work,

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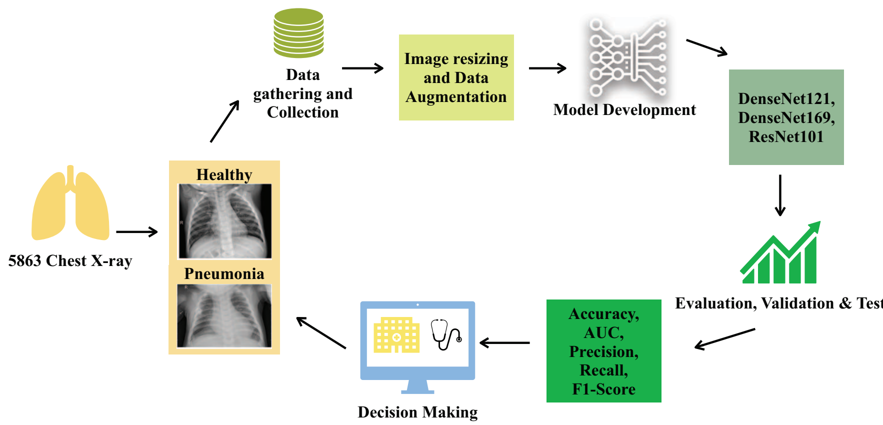

Fig. 1: The prediction process encompasses data gathering, where ongoing data preparation and quality enhancements occur, model development involving iterative fine-tuning and adjustments, and evaluation, where overlapping phases are effectively managed. This leads to informed decision-making based on refined predictions.

consisting of 5856 chest X-ray images, is the same dataset we utilized in our research. The study reported accuracies of 87.78% for CNN, 88.94% for InceptionResNetV2, 90.7% for Xception, 91.66% for VGG16, 87.98% for ResNet50, and 94.02% for EfficientNetV2L achieving the highest accuracy. These results underscore the effectiveness of deep learning models especially EfficientNetV2L in the precise detection of pneumonia from chest X-rays, providing essential support for enhancing patient care and helping clinical decisions.

Zhenjia et al. [15] applied several Convolutional Neural Network (CNN)-based models including MobileNet [16], CNN, ResNet-18 [17], along with two additional widely-recognized CNN frameworks that were pre-trained using the ImageNet [18]. These two models are the deeper and more complex ResNet50 [17] and the VGG19 [12]. The dataset used in their study was collected from Kaggle chest X-ray images (Pneumonia) including 5,216 training images and 624 test images divided into two classes normal and pneumonia for binary classification. The evaluation results indicate that each of the five deep learning models was able to detect pneumonia. However, MobileNet achieved the highest validation accuracy 87%, and loss value of 0.25 in comparison with other models. The author concluded that deep learning models typically have several parameters and calculations, making them impractical for embedded devices. However, for the early detection of pneumonia, especially in regions with limited medical resources, MobileNet is recommended due to its efficiency. Additionally, applying automatic detection in pneumonia X-ray image diagnosis can decrease pneumonia mortality rates, provide patients with faster treatment, and reduce the workload of radiologists.

In a different study Anggit et al. [19] used CNN and transfer learning InceptionV4 model to differentiate COVID-19 [20], [21] patients from healthy individuals by detecting symptoms of pneumonia in chest X-ray images. The dataset used in their study includes 5,232 images from Kaggle chest X-ray images labeled by a medical expert. The dataset is split into training and testing sets for patients categorized into pneumonia with 3883 images and Normal with 1349 images. The study reported Inceptionv4 model achieved superior performance with an average recall of 100% and an accuracy of 88%. As highlighted by the authors the efficiency of diagnosing pneumonia through visual inspection by radiologists is low. Therefore, employing artificial intelligence particularly Convolutional Neural Networks (CNNs) for analyzing clinical images is important. Deep learning models can identify chest X-ray images more accurately and rapidly than human interpretation.

Taking a different method and utilizing a specific CNN-based model Dhayanithi et al. [22] employed LeNet classifier to classify pneumonia versus normal cases. The performance results of the model are evaluated using extensive public chest X-ray images and compared against relevant deep learning benchmarks. During training, 4,684 images, including both pneumonia and non-pneumonia cases are utilized. For validation and testing 1,152 and 20 images are respectively employed. The findings of this study show an outstanding recognition accuracy of 96% in detecting pneumonia from chest X-ray images. This study demonstrates that the Concatenated Modified LeNet classifier model could be a valuable tool for healthcare professionals in diagnosing pneumonia, increasing the accuracy and speed of image analysis, which may lead to better treatment decision-making and patient results.

Our study employs three high-performing deep transfer learning (DTL) models to detect pneumonia significantly improving diagnostic accuracy over previous studies. These models show enhanced detection capabilities, reducing both false positives, and false negatives crucial for reliable diagnostics [23]. Additionally, we provide a comparative analysis of these models to identify the most effective approach under varying conditions, assisting healthcare practitioners in selecting the best model for specific clinical scenarios. The use of multiple models also ensures broader validation, increasing the generalizability and robustness of our results across diverse populations and imaging technologies. Overall, our research advances diagnostic precision and aids the physician in their decision-making.

Effectiveness of Deep Learning Models– What are the advantages of transfer learning models in detecting pneumonia

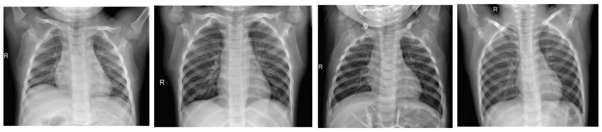

Fig. 2: Sample chest X-ray images of healthy patients

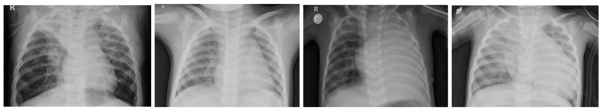

Fig. 3: Sample chest X-ray images of patients with pneumonia

from chest X-ray images compared to medical experts?
Clinical Integration– How do deep learning models for binary classification of pneumonia impact clinical workflows and patient outcomes, and how can these insights assist clinicians in their decision-making process?
We used different deep transfer learning (DTL) methods to evaluate how well predictive models can identify early diagnosis of pneumonia through abnormalities for chest X-ray analysis. Deep learning models for binary classification of pneumonia have shown significant efficacy in enhancing clinical workflows by offering quick and accurate diagnostic insights, as evidenced by our study's results. These models provide clinicians with a robust diagnostic tool, contributing to more precise decision-making and enabling expedited and accurate treatment choices. The improvements in diagnosis speed and reliability suggested by our findings indicate a potential for better patient recovery rates and shorter hospital stays. We recommend further integration of these models into clinical practices to leverage their full potential in improving patient outcomes.

II. Methods and Materials

Figure 1 shows a comprehensive methodology applied in our research, emphasizing the main goals of our study which are to examine the effectiveness of deep learning in detecting pneumonia and to help the practicality of this technique for pneumonia detection. In greater detail, this figure outlines the input data, preprocessing techniques, deep learning (DL) models utilized for training our dataset, and validation and testing metrics implemented to evaluate the performance results of our research. Additionally, it includes the decision-making process by radiologists highlighting how they integrate the model's insights into their clinical judgments.

A. Dataset and Data Preparation

Dataset–To develop and evaluate our deep learning algorithm for detecting pneumonia, we used a publicly available dataset of chest X-ray images obtained from historical patient cohorts aged between one and five years old from the Guangzhou Women and Children's Medical Center in China [24]–[26]. The dataset includes a total of 5,863 gray-scale chest X-ray images including 4,280 are labeled as illustrating pneumonia, while the remaining 1,583 images are classified as normal. Figure 2 and Figure 3 show sample grayscale chest X-ray images from healthy individuals and pneumonia patients, respectively.
Data Preparation– Given that image processing serves as the foundational data source for performance evaluation in this study, some image preprocessing techniques were applied before using the data in the training. Notably, this preparatory phase contained both the resizing of images and the application of data augmentation techniques:
1) Resizing: Chest X-ray images are widely recognized and used as the predominant clinical technique for the diagnosis of pneumonia. An input image is included by three parameters: $W \times H \times C$. Here, W denotes the width, H shows the height, and C represents the number of channels [27]–[29]. Chest X-ray images, including those used for pneumonia diagnosis, are usually gray-scale images. In the field of medical imaging, gray-scale is preferred because it adequately captures the required anatomical details and contrasts needed for diagnosis without the complexity of color information. Each image typically consists of a single channel that represents varying intensities of black, white, and gray which is necessary for detecting different tissues, abnormalities, or lung diseases including pneumonia [30]. Ensuring consistency in the size of our input data with those utilized in pre-train models, we standardized the size of our input data to $320 \times 320 \times 1$ for compatibility with the DenseNet121, DenseNet169, and ResNet101 models in the training set. To increase the efficiency of the learning process, we additionally adjusted the size of the remaining images in the testing set to $255 \times 255 \times 1$.
2) Data Augmentation: We used image random rotation, vertical, and horizontal flipping to reassemble possible chest X-ray orientation deviations. To improve preprocessing efficacy for the publicly available pneumonia chest X-ray images composed of gray-scale images, we implemented pixel value normalization by re-scaling the images with a multiplication factor of 1/255. This adjustment standardized the pixel value range to between 0 and 1. Additionally, to increase our training dataset, enhance model performance, and improve the predictive models' generalizability, the `torchvision.transforms` library in `PyTorch` [31] was used for the application of data augmentation techniques.

B. Predictive Models

Deep learning (DL) represents the cutting-edge approach in machine learning models, wherein data is comprehended through its progression across multiple layers that integrate non-linear operations [32], [33]. To address the challenges of feature engineering and mitigate over-fitting during the hyperparameter tuning phase of the training process, deep learning (DL) models benefit significantly from extensive datasets. To do this, we utilized transfer learning (TL) techniques leveraging knowledge from large-scale pre-trained models. This approach not only helps in avoiding over-fitting but also in decreasing computational time and complexity, enhancing the efficiency and effectiveness of our model development [28], [34], [35]. Therefore, we employed some of the most high-performing pre-trained transfer learning models including DenseNet121 [36], [37], DenseNet169 [37], and ResNet101 [17].

1) Configurations: In our binary classification of pneumonia, we replicated the training and evaluation process using two different batch sizes 32 for DenseNet121, and 64 for DenseNet169 and ResNet101 [38]. This variation in batch sizes chosen due to the different sizes of our transfer learning models, aimed to enhance their generalizability. To determine our model's performance was not due to overfitting, we plotted the accuracy and loss metrics across all epochs. We utilized Scikitlearn [39], Python 3.10 [40], and PyTorch 2.1 [31] to train, validate, and test 1.27 GB of data including 5863 gray-scale chest X-ray images in Google Colab Pro with NVIDIA Tesla P100 GPU. In this research, we utilized values of accuracy and loss to train, validate, and test the efficacy of our developed predictive models. We also experimented with varying the hyperparameters to optimize the configuration of these models. In our customized deep learning models, we found that using the `Adam optimizer` with a learning rate of 0.0001 could achieve the best results [28], [41]. To mitigate the problem of data imbalance in our dataset, we applied weighting [42]. furthermore, we utilized a pre-trained ImageNet model to enrich the context during training, which enhanced both the speed and precision of learning [18]. We initially set the training to 54 epochs to achieve optimal accuracy across the training, validation, and testing phases. However, the results show no further enhancements beyond certain points so we adjusted fewer epochs to optimize computational resources [43]. To keep the pre-trained layers unchanged and reduce computation time across each transfer learning model, we modified the network by freezing the initial layers, excluding the fully connected layer. We then replaced the final layer with a new one tailored for our binary classification task [44].

2) Classification Models: This section provides insights into the deep transfer learning techniques we customized and fine-tuned to meet the particular needs of our study and dataset. To classify the chest X-ray dataset to detect pneumonia in our research, we utilized three high-performing pre-trained transfer learning models DenseNet121, DenseNet169, and ResNet101. Every pre-train model has a distinct sized input layer defined on torchvision documentation [45]. In all deep learning models batch normalization [46] and Dropout layer [47] are applied to regularize and improve the performance of CNNs models in PyTorch. We applied `weight_decay` known as L2 regularizer [48] to prevent overfitting, minimize the loss value, and increase the performance. A ratio of 0.63, 0.27, and 0.10 was applied to split the dataset into training 3651, validation 1565, and testing 624 gray-scale chest X-ray images.

III. Results and Discussions

Figure 4 shows the confusion matrices for the training, validation, and testing DenseNet121 model in binary classification. It also presents plots of loss and accuracy indicating

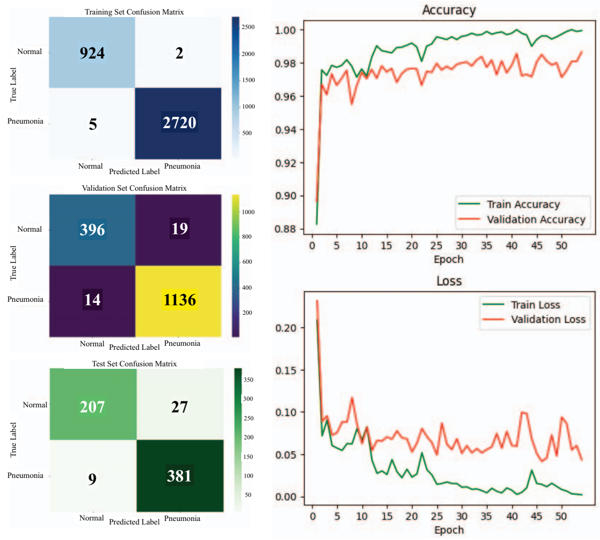

Fig. 4: The performance and confusion matrix results of the binary classification of pneumonia using the DenseNet-121 model

TABLE I: Training and Validation Results of DL Models in pneumonia Classification

Method	Train acc	Val acc	Train loss	Val loss
DenseNet121	99.4%	98.68%	0.002	0.04
DenseNet169	99.84%	98.36%	0.004	0.05
Resnet101	98.51%	97.69%	0.03	0.06

the model's generalizability and confirming is not a result of overfitting, and it received the highest accuracy of 98.68%, and a loss value of 0.04.

Figure 5 demonstrates both labeled and predicted chest X-ray images used in the binary classification of pneumonia with the DenseNet121 model on the test set. The results show that the model can accurately and effectively predict both classes.

Table I presents the the training and validation performance results of the models implemented in this study including DenseNet121, DenseNet169, and ResNet101. The highest validation accuracy of 98.68% with a low loss value of 0.04 was achieved by the DenseNet121 model. DenseNet169 achieved an accuracy of 98.36% in validation with a loss value of 0.05, while ReseNet101 achieved an accuracy of 97.69% in validation with a loss value of 0.06.

Table II shows the evaluation metrics for the binary classification of pneumonia on the test set. As shown, the DenseNet121 model achieved the highest test accuracy 94%, AUC 93%, Precision 93%, Recall 98%, and F1-Score 95% respectively. DenseNet169 achieved a test accuracy 93%, AUC 91%, Precision 90%, Recall 99%, and F1-Score 94%. Lastly, ResNet101 received the lowest test accuracy 92%,

TABLE II: Evaluation metrics of DL models in the binary classification of pneumonia on the test set

Method	Test acc	AUC	Precision	Recall	F1-score
DenseNet121	94%	93%	93%	98%	95%
DenseNet169	93%	91%	90%	99%	94%
ResNet101	92%	89%	89%	99%	94%

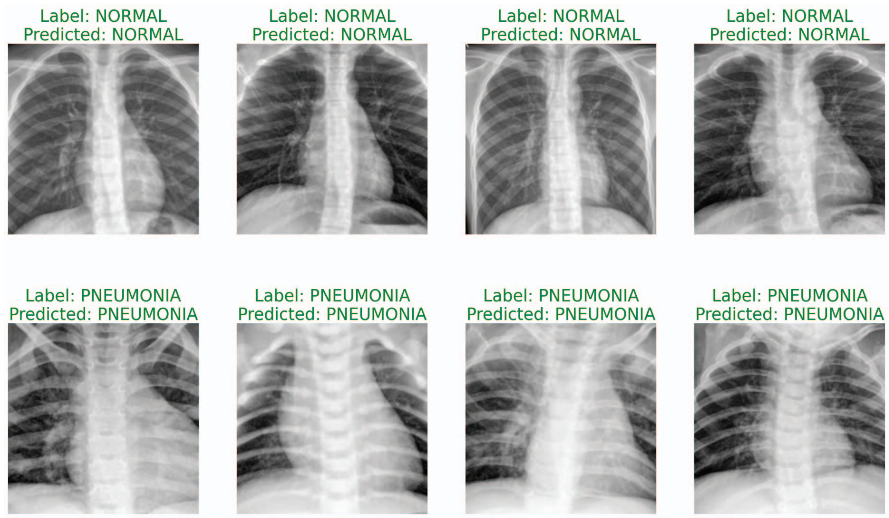

Fig. 5: Labeled and predicted chest X-ray images for pneumonia and normal cases using DenseNet121 on the test set

AUC 89%, Precision 89%, Recall 99%, and F1-Score 94%.

A. Key Findings

In this research, we assess how well our transfer learning models could differentiate between pneumonia and healthy cases using gray-scale chest X-ray images in a binary classification task. Our study, as presented in Table I showed that deep transfer learning (DTL) models are highly effective in the early detection of pneumonia in gray-scale chest X-ray images with a validation accuracy of 98.68% and a loss of 0.04. We achieved this level of result by using DenseNet121, which performed better than other pre-train models we evaluated in our study. This recommends that deep learning models could be really helpful for radiologists to detect pneumonia in the early stage of the disease.

B. Limitations

There are several limitations should be noted in this study. We adjusted the hyperparameters of our predictive models to manage the training, validation, and testing of the pre-trained models and define their configurations. For instance, due to limited computational resources, we set the epochs for our deep learning model to fewer than 55. This limitation may impact the model's learning capabilities, potentially reducing the loss value and helping to avoid overfitting. Nonetheless, the model's high performance in binary classification and the consistent loss and accuracy metrics (Figure 4) show that increasing the number of epochs might not significantly alter the findings of this study. In this study, the gray-scale chest X-ray images we utilized had different consistency and quality, affecting model training and performance. Variations in imaging protocols, cameras, patient positioning, and image size can introduce biases and impact the model generalization across different clinical settings. But, to improve the generalization and accuracy of our pre-train models, several Image processing techniques were used to address this issue. The chest X-ray datasets we used in this work show a class imbalance with a high prevalence of pneumonia cases compared to normal cases. This imbalance can lead to models that are biased toward predicting the majority class, potentially reducing sensitivity to normal cases. therefore, To address data imbalance in our dataset, we implemented weightings.

IV. Conclusion and Future Work

Diagnosing pneumonia in the early stages from chest X-ray images poses significant challenges for radiologists in the timely treatment of patients. This study focused on creating an automated algorithm using convolutional neural networks (CNNs) with pre-trained models (e.g., DenseNet121, DenseNet169, and ResNet101) for pneumonia detection in chest X-ray images. Prior to this, we carried out several pre-processing procedures and adjusted the parameters of each model individually. Our results show that DenseNet121 surpassed other pre-train models in classifying pneumonia accurately, achieving a 98.68% validation accuracy rate and the lowest loss value of 0.04. The findings of this study could offer valuable insights to enhance pneumonia detection, make diagnostic results clearer, and help radiologists in the decision-making process. In future studies, we intend to utilize ensemble learning, combining predictions from our pre-train models with optimal weighting to enhance generalizability and accuracy. We plan to use larger and more diverse datasets to train, validate, and test our pre-train models to improve their statistical robustness and generalizability across different populations and settings. We intend to use interpretable deep learning models such as Grad-CAM [49], LIME [50] and SHAP [51] to make the decision-making process of the AI models more transparent and understandable for clinicians by increasing usability and trust in the clinical settings. Lastly, we aim to implement clinical trials and real-world studies to confirm the effectiveness and reliability of our transfer learning models in real healthcare environments, evaluating their effects on patient outcomes and diagnostic processes. We think our research can assist in the early diagnosis and detection of pneumonia and improve results interpretation.

V. Acknowledgement

The chest X-ray images for detecting pneumonia utilized in this study are used under the Creative Commons Attribution 4.0 International License (CC BY 4.0). Appropriate credit has been given, a link to the license is provided [52], and any modifications made to the original images have been noted.

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