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Transfer Learning Based CNN And LSTM Models For Water Body Identification And Water Level Forecasting

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Abstract*—Water bodies identification and Water level prediction is very important for water resource management to lower the risk of flood, and to protect the environment. This research tries to explore how deep learning and transfer learning can be used to perform these tasks by using satellite images. The primary challenge for accurately predicting water levels and identifying water bodies in satellite images is the temporal variations in weather conditions. Convolutional neural networks (CNN) are efficient while working with images. Long-Short-Term Memory (LSTM) models are also good at prediction of water levels. For water body identification, CNN-based models achieved upto 95% accuracy and for Water level prediction LSTM networks also reached upto 95% accuracy. Transfer learning is a machine learning technique where a model trained on one task can be reused as the foundation for a another task. By using Transfer learning methods, the accuracy of these models can be improved. This method minimizes the cost of computing resources and the training time. The results highlight that combining deep learning methods with transfer learning methods can improve the accuracy for these tasks. The proposed method suggests a strong direction to accurately predict water levels and identify bodies of water, which will help to water resource management. Use of satellite images with deep learning and transfer learning models offers a better solution to explore its uses in hydrological and environmental science.*

Index Terms*—Water Level Forecasting, Water Body Identification, Machine Learning, Transfer Learning*

INTRODUCTION

Water level prediction and water bodies identification are important aspects of hydrology and water resource management. Accurate and comprehensive analysis of data can make a significant difference in water resource management. Extracting data from satellite images requires complex computational techniques, such as deep learning models. Predicting water levels accurately is challenging due to extreme events. Floods can occur when water levels rise, forcing people to leave their homes and putting lives at risk. Accurate forecasting of water levels help authorities to act quickly to minimize these risks [1]. Traditional forecasting methods, which based on physical and conceptual models, are not exceptionally good at managing complex and varying size of water bodies. Satellite images offer detailed view of water bodies. However, the use of satellite images is hampered by variable climate conditions and the sheer volume of data involved. In addition, on large scales, manual analysis becomes impractical, which requires reliable and automated identification techniques [2]. In image analysis, machine learning, CNNs has shown outstanding performance. CNNs can automatically learn features from images, enabling them for water bodies identification in satellite images. It offers strong performance in differentiating between water and non-water bodies because for training it requires large datasets. However, for training of CNNs requires more time and computational resources. The efficiency of this process can be improved with use of transfer learning. Transfer learning models can be fine-tuned and made more adaptable to current domain [3]. LSTM systems have emerged as great at predicting water levels. LSTMs are designed to work with time-series information. LSTM networks can make accurate predictions by obtaining valuable information from historical data and characteristic variable values. The use of CNN, LSTM, and transfer learning methods together maybe a solid approach for improving accuracy in predicting water levels and identifying water bodies at data scarce regions. This integrated methodology helps the Water Resource Department to make good choices and use their resources more effectively [4].

RELATED WORK

Satellite images and machine learning methods have made huge developments in hydrological studies. Hydrological study also involves some tasks like Predicting water levels and identifying water bodies. In the past, these tasks were performed with readings taken on the ground and by using different hydrological models such as physical models, conceptual or empirical models, etc. However, these models often not accurate and adapt to changing weather conditions. To solve these problems, recent studies have used satellite data and more powerful computational methods. Many researchers used recurrent neural networks (RNNs) and their variations, like LSTMs, because they can handle time-series data. LSTMs can accurately predict water levels by analyzing past data and natural factors. They perform it better than standard statis- tical methods.[5]. Similarly, a mixed method that combines LSTM networks with physical water models has been used to make predictions more accurate, especially in places that does not have a lot of past data [6]. CNNs have also useful for identifying bodies of water using satellite Images. A deep learning approach was used to accurately identify bodies of water in multi-spectral satellite Images, even when there was noise was present in the images [7]. The combination of transfer learning techniques has been used to improve further performance. Transfer learning using pre-trained CNN models reduces computational requirements and training time, while preserving high accuracy [8]. Putting together different data sources and methods is another vital aspect for such type of work. Predictions of water levels are more accurate when satellite images and sensor data from the ground are combined. This method gives complete analysis how the water moves [9]. Similarly, combining visual and radar. satellite images to identify bodies of water shows that combining data from multiple sensors can improve the accuracy in a different weather condition [10]. Transfer learning has been used to make a CNN model that was already trained. Work better for classifying bodies of water in different parts of the world, with huge improvements in accuracy with less extra training [11]. Transfer learning also improves the accuracy of LSTM networks in predicting water levels by using models that already been trained in similar hydrological applications [12]. Even with these improvements, there are still problems with using machine learning and transfer learning for water studies [13]. Several challenges exist, such as variations in satellite image quality, differences in sensor performance, and temporal changes in water bodies. Another major problem is that fine- tuning of deep learning models still needs a lot of large samples that have been labeled [14]. To address these challenges, continued research and the development of novel methods capable of operating across diverse environments and varying data volumes are required. Table 1 presents summary of the related work done in water level forecasting and water body identification.

Table 1. Summarizes the related work in water level forecasting and water body identification

Method	Approach	Key Finding	Area	Limitation	Scope
LSTM Networks [15]	Analyzing historical data and environmental factors	Outperformed traditional statistical methods	River water levels	Requires large datasets and computational resources	Applicable to various time-series forecasting tasks
Hybrid LSTM and Physical Models [16]	Combining LSTM with hydrological models	Enhanced forecast accuracy in regions with limited data	Diverse hydrological regions	Complexity in integrating models and data sources	Improved predictive capabilities in data-scarce regions
CNN for Image Classification [17]	Using CNNs to classify water bodies from multi-spectral images	High accuracy and robustness against noise	Multi-spectral satellite images	High computational cost for training	Automated large-scale water body identification
Transfer Learning with CNN [18]	Applying pre-trained CNN models	Reduced computational resources and training time	Various geographical regions	Dependency on pre-trained models and domain-specific fine-tuning	Efficient model adaptation to different environments

Satellite and Ground Data Integration [19]	Combining satellite imagery with ground-based sensor data	Improved reliability of water level forecasts	Water dynamics monitoring	Complexity in data integration and processing	Need of Efficient models for data integration
Optical and Radar Image Fusion [20]	Fusing optical and radar satellite images	Enhanced accuracy under varying conditions	Multi-sensor data integration	Requires advanced data fusion techniques	multi-sensor data utilization can be improved
Transfer Learning for Water Body Classification [21]	Adapting pre-trained CNN models for specific regions	Significant accuracy improvement s with training	Geographical regions	Limited by availability of suitable pre-trained models	Efficient classification across different regions
Transfer Learning with LSTM [22]	Incorporating pre-trained models from related hydrological applications	Enhanced predictive capabilities of LSTM networks	Hydrological applications	Dependence on quality and relevance of pre-trained models	Water level forecasting accuracy can be improved

DESCRIPTION OF DATASET

The “Satellite Images of Water Bodies” dataset, available on Kaggle, is a valuable resource for image segmentation. This dataset contains a collection of satellite images along with corresponding masks that delineate the water bodies within each image [23]. It is curated to support environmental monitoring and hydrological studies. Every image in the dataset is paired with a binary mask, where pixels corresponding to water bodies are distinctly marked from the surrounding landscape. This clear segmentation facilitates the training of machine learning models, particularly CNNs, for accurate image segmentation. Sample images from the dataset are shown in Fig. 1. The availability of labeled allows researchers to bypass the labor-intensive process of manual annotation, fast-tracking the development, and make use of valid image analysis algorithms. The dataset’s images capture diversified geographic regions and different climatic conditions, providing a wide range of scenarios. This diversity plays main important role for creating robust models capable of generalizing across different geographic regions and environmental conditions. The high-resolution images improve a model’s ability to detect fine details, to contribute more accurate for segmentation results. A key advantage of this dataset is its relevance to transfer learning. Researchers can leverage pre-trained models on this dataset to improve performance on similar tasks with limited data availability. This approach reduces computational costs while enhancing model accuracy.

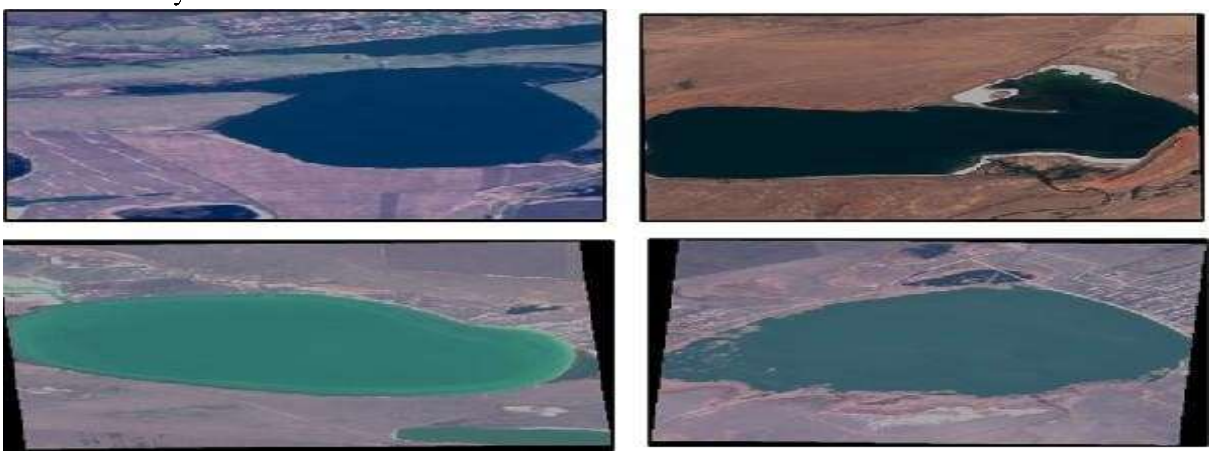

Fig. 1. Sample Images of Dataset

PROPOSED METHODOLOGY

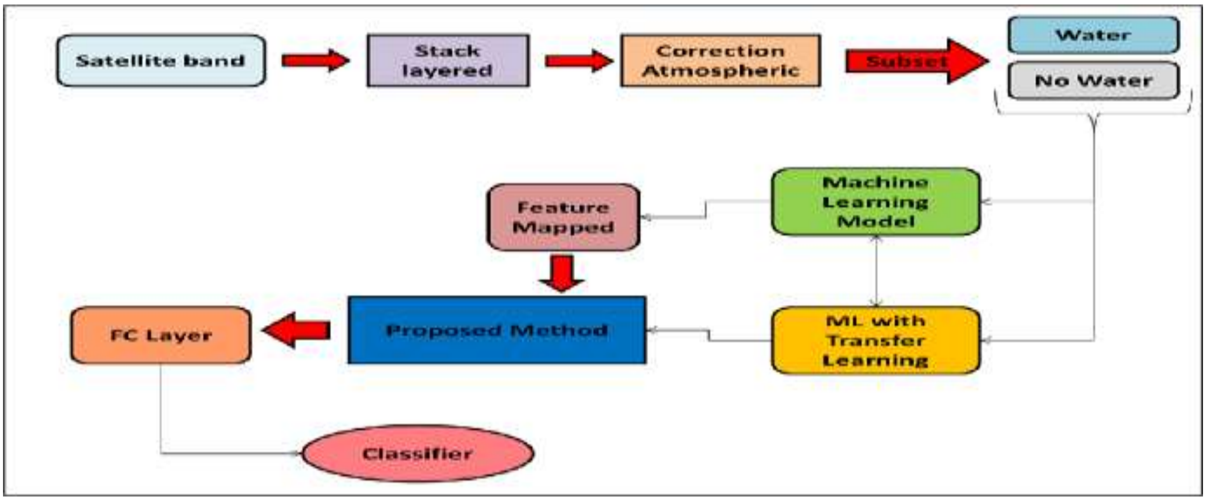

Fig. 2. Overview of Proposed Model for Prediction and Detection

The proposed strategy, as illustrated in figure 2, leverages both machine learning and transfer learning approaches to improve water body identification and water level estimating utilizing images. The machine learning approach is separated into two fundamental components: CNNs and LSTM systems. For water body differentiation, CNNs are utilized, due to their capability in image classification and division assignments. By using pre-trained models such as ResNet50, InceptionV3, MobileNetV2, and EfficientNetB0, the approach leverages the extensive feature extraction capabilities of these architectures. These models, pre-trained on ImageNet, are fine-tuned on the specific satellite images and masks dataset. This fine- tuning alters the pretrained weights to suit the unused dataset, accomplishing high precision and proficiency in recognizing water bodies. Within the domain of water level prediction, LSTM systems are used for their quality in dealing with time-series information. The technique includes utilizing pretrained LSTM models, or preparing LSTM systems on related hydrological time-series information, to figure out water levels accurately.

1.1 Deep Learning Approach

- CNN

CNNs are widely recognized for their effective- ness in image classification and segmentation tasks. They are performing better at detecting spatial features within images through their layered architecture, which mimics the human visual processing system. For water body identification, CNNs can process images to accurately distinguish between water and non-water regions. By training on a large dataset of labeled images, CNNs extract patterns and features for identifying water bodies. This approach significantly reduces the manual work required for water body identification job.

- LSTM

LSTM networks are specially designed to process time-series data and long-term dependencies within the data. LSTMs can extract temporal dependencies in water level information by considering factors such as seasonal changes, and current trends. LSTM models can be trained on large time-series datasets, to forecast future water levels with more accuracy. This capability will be helpful for water resource departments in decision making about water resources.

1.2 Transfer Learning Approach

Transfer learning utilizes pretrained CNNs to improve precision and effectiveness in water body identification. Models such as ResNet50, InceptionV3, MobileNetV2, and Efficient- NetB0, trained on huge datasets like ImageNet. They are fine-tuned utilizing images of water bodies. Transfer learning approach includes updating the pre-trained weights to adopt to the modern dataset, both together minimizes efforts and preparation from scratch.

This study also explores the following pre-trained models that can be used for water bodies identification.

- ResNet50

ResNet50, is a particular variation of the Residual Neural Network (ResNet). ResNet is more efficient in

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extracting valuable information from satellite images. ResNet50 can be fine-tuned on other water bodies dataset by adjusting its pretrained weights to identify water bodies with more accuracy. The ability to process complex data and reduction of the gradient vanishing problem makes it more suitable for hydrological applications [24].

- InceptionV3

Initial modules of InceptionV3 captures multiscale features within images. InceptionV3 can be fine-tuned on various image datasets, due to their robust feature learning This approach minimizes required training time. IncetionV3 can process diverse and complex visual patterns. It also appears as a strong alternative for hydrological applications. It also ensures accurate identification of water bodies under varied environmental conditions [25].

- MobileNetV2

The MobileNetV2 has become strong choice for hydrological applications in resource constrained areas. It has lightweight and efficient architecture. MobileNetV2 obtains greater efficiency due to Depth wise separable convolutions and inverted residual block with linear bottlenecks. It is also trained on ImageNet. It also minimizes computational complexity and maintains high accuracy [26].

- EfficientNetB0

EfficientNetB0 is powerful and versatile CNN. It is also useful for hydrological applications. It uses a compound scaling strategy. It is lightweight compared to larger CNNs but performs well on visual recognition tasks, making it good for large scale hydrological image datasets. It is also pre-trained on ImageNet [27].

The study also investigates the following pre-trained models for forecasting water levels.

- LSTM Networks with transfer learning

LSTM networks are specially designed for time series forecasting. They can be used for predicting water levels based on previous historical data and current data. With the help of transfer learning methods, LSTMs can use trained models from related hydrological task to another task, also improving accuracy, and reducing training time. LSTM networks capture temporal dependencies and patterns in water level data, considering various factors such as seasonal variations and current trends. When combined with feature extraction from images, it provides robust and accurate predictions. These predictions can be helpful in decision-making for water resource departments. Further transfer learning strengthens the capabilities of LSTMs. It emerges as a versatile model for accurate forecasting of water levels under diverse and complex environmental conditions.

- Hybrid Models Combining LSTM with CNNs

Hybrid models that combine LSTM and CNN architectures offer an efficient approach for comprehensive analysis of water and water level estimation. CNNs extracts spatial information from images, identifying patterns and examines changes in water bodies, whereas LSTM networks analyze temporal trends in water level data. This integrated approach combines the advantages of both models to improve the accuracy and robustness of the forecast.

RESULT AND DISCUSSION

Table 2. Performance metrics and results for the water body extraction using CNN and LSTM ML Model

Model Parameters	Value
CNN Accuracy	95.2%
CNN Precision	94.8%
CNN Recall	95.5%
LSTM MAE (Mean Absolute Error)	0.08 meters
LSTM RMSE (Root Mean Square Error)	0.12 meters
LSTM R2 Score	0.92
F1 Score (CNN)	95.1%
Training Time (CNN)	4 hours

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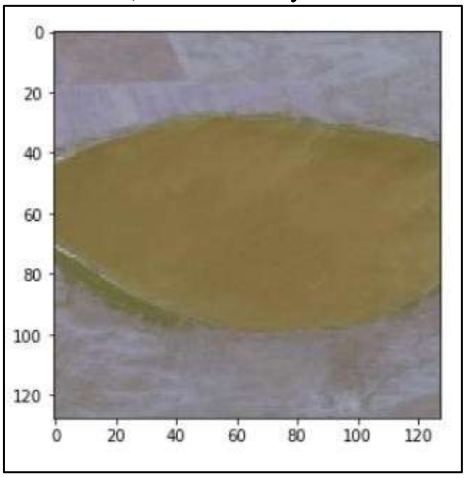
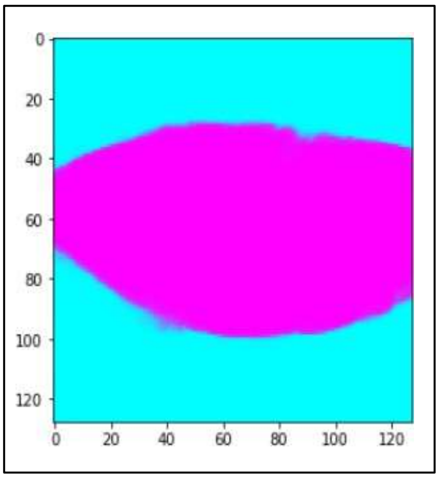
Training Time (LSTM)	2 hours
Inference Time (Per Image - CNN)	0.02 seconds
Inference Time (Per Prediction - LSTM)	0.01 seconds

Table 2 presents the performance metrics and results for the extraction of water bodies using a CNN and LSTM model. CNN achieved an accuracy of 95.2%, representing its effectiveness in detecting water bodies from images. It has achieved a precision of 94.8% and the F1 score is 95.10%. The LSTM reflects its precision in water level forecasting with a MAE of 0.08 meters RMSE of 0.12 meters. The LSTM R2 score is 0.92. For training CNN and LSTM models require 4 and 2 hours, respectively, with inference times of 0.02 seconds per image for the CNN and 0.01 seconds per prediction for the LSTM. These values show CNN's and LSTM's high computational efficiency.
The original image is shown in Figure 3 (a). In Figure (b), you can see the projected mask that the CNN model made, which clearly shows the named bodies of water.



(a)



(b)

Figure 3: (a) Original Image (b) Predicted Mask

Table 3 presents a comparative analysis of a hybrid CNN+LSTM model and various CNN architectures for the water bodies identification. The Comparison has been performed using confusion matrix. Accuracy, precision, recall, and F1 score of the confusion matrix have been used to evaluate the performance of model. ResNet50 obtained an accuracy of 95.2%, for distinguishing water bodies in satellite images. InceptionV3 and MobileNetV2 achieved the accuracy of 94.8% and 94.5%, respectively, while EfficientNetB0 achieved slightly better accuracy than them with 95.0%. The hybrid CNN+LSTM model obtained the best performance, obtained 97.2% accuracy. In terms of precision, ResNet50 scored 94.8%, InceptionV3 obtained 94.3%, MobileNetV2 got 94.0%, and EfficientNetB0 obtained 94.6%, while the CNN+LSTM model achieved 96.9%. This higher precision indicates that the hybrid model has the better capability in accurately detecting water bodies. For recall, ResNet50 reached 95.5%, InceptionV3 got 94.9%, MobileNetV2 obtained 94.7%, and Effi- cientNetB0 95.2%. For F1 score, ResNet50 achieved 95.1%, EfficientNetB0 obtained 94.9%, InceptionV3 got 94.6%, and MobileNetV2 got 94.3%, while the CNN+LSTM model again performed better than all others with a leading score of 96.8%, which indicates its balanced and robust performance on both precision and recall metrics.
Table 3. Comparison of Different Models Based on Various Metrics

Metric	**ResNet50**	**InceptionV3**	**MobileNetV2**	**EfficientNetB0**	**Hybrid (CNN + LSTM)**
Accuracy (CNN)	95.2%	94.8%	94.5%	95.0%	97.2%
Precision (CNN)	94.8%	94.3%	94.0%	94.6%	96.9%

Recall (CNN)	95.5%	94.9%	94.7%	95.2%	97.0%
F1 Score (CNN)	95.1%	94.6%	94.3%	94.9%	96.8%

Figure 4 presents graphical accuracy comparison of different methods

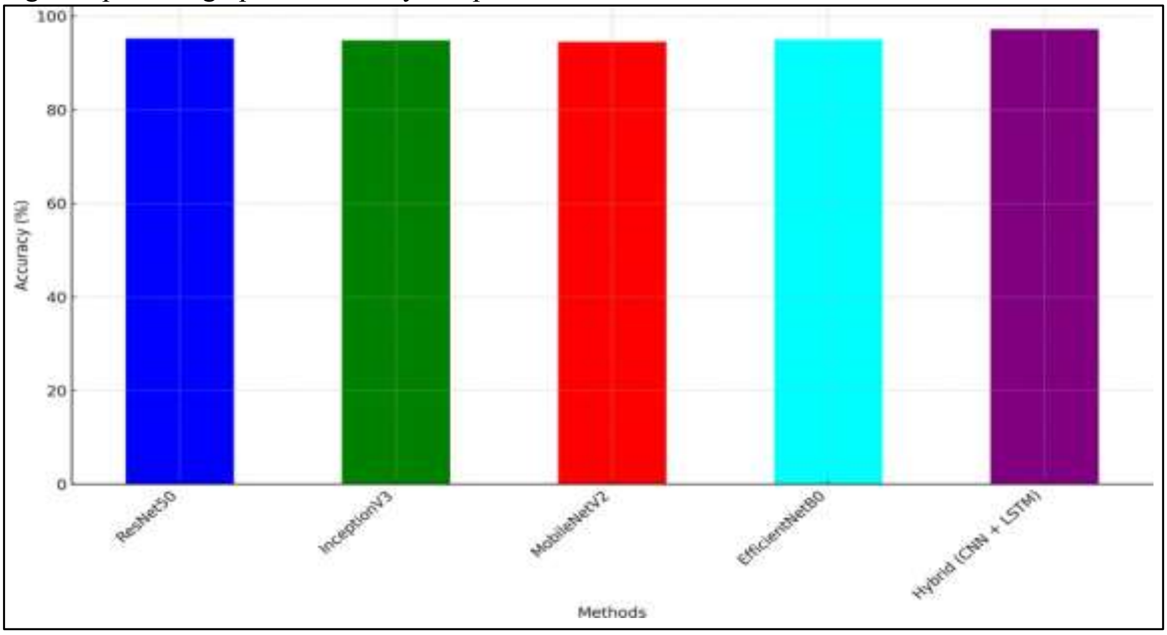


Figure 4: Accuracy Comparison of Different Methods

CONCLUSION

Using advanced CNN architectures such as ResNet50, InceptionV3, MobileNetV2, and EfficientNetB0, this study presents the ability of these models to accurately differentiate between water bodies. CNN models show their robustness in handling complex image analysis tasks, as these models achieved high precision, accuracy, recall, and F1 scores. Furthermore, integrating CNNs with LSTM networks improved performance, particularly in water level forecasting. The CNN+LSTM approach takes advantage of the spatial feature extraction capabilities of CNNs and the temporal sequence modeling capabilities of LSTMs. Transfer learning played a significant role in enhancing model performance while reducing computational costs and training time. The pre-trained models trained on ImageNet dataset provide a solid foundation for extracting features and fine-tuning on specific satellite image datasets, ensuring the generalization and efficiency of models. Using advanced techniques like machine learning, deep learning, and transfer learning in the hydrology area ensures a more accurate analysis of water bodies, helping water resource departments make decisions to mitigate flood risks. Future work will explore more advanced and hybrid architectures. Also evaluates these models across diverse regions to verify their generalizability, thereby helping researchers design robust and generalized solutions.

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