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Conv-Ensemble for Solar Power Prediction With First Nations Seasonal Information

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ABSTRACT Power generation forecasting, especially for solar power, is crucial for future energy planning. In this study, a novel framework, namely *FNS-Metrics*, is proposed to integrate seasonal information from First Nations calendars into solar power forecasting. Furthermore, a novel Conv-Ensemble framework is proposed, leveraging the high-level feature extraction capabilities of Conv1D layers along with the low-level feature extraction abilities of transformer and LSTM networks. A weighted feature concatenation technique is also integrated into the proposed approach to combine the features effectively. To validate the proposed FNS-Metrics and Conv-Ensemble framework, a new dataset is constructed by collecting power and weather data from the Desert Knowledge Australia Solar Center in Alice Springs and integrating data related to First Nations seasonal cycles. Experiments on this dataset show that the Conv-Ensemble framework with FNS-Metrics outperforms traditional approaches, achieving state-of-the-art solar power prediction with the highest R^2 of 0.8641 and the lowest MSE of 22.41. These represent a 14.60% and 26.21% increase compared to the baseline configuration of Conv-Transformer. The ablation study demonstrates that the Conv-Ensemble framework improves performance compared to the baselines. Furthermore, the results for individual and combined FNS-Metrics features show a progressive improvement in performance.

INDEX TERMS Deep learning, first nations seasons, LSTM, solar power forecasting, transformer.

I. INTRODUCTION

The global energy landscape is experiencing an extreme transformation as the world moves from fossil fuel-based power generation to renewable energy sources. Traditional power generation systems, dominated by coal, natural gas, and oil, have long been associated with adverse environmental impacts, including greenhouse gas emissions, air pollution, and climate change [1]. In response to these challenges, there has been a growing interest in adopting green energy solutions, such as solar, wind, tidal and biomass energy. Among these, solar power systems have emerged as a prominent renewable energy source due to their scalability, reduced costs, and potential for integration into residential and commercial settings. In Australia, solar energy production is highly feasible because the country has the highest average solar radiation per square meter of any continent in the world [2]. Despite installation and infrastructure challenges, northern and central Australia hold great promise for solar energy.

Solar energy lacks long-term persistence due to variations in solar irradiation across time and location. Geographic differences significantly affect solar power generation; for instance, India and Australia exhibit distinct patterns throughout the year [3], [4]. Accurate solar power prediction is challenging due to the complex interplay of weather, atmospheric conditions, and the dynamic nature of solar irradiance. These challenges hinder the development of a universal prediction model. However, accurate predictions are essential for improving power supply reliability and optimising energy management. Solar power forecasting has also gained economic importance with the global rise in solar energy use [5]. Advances in Machine Learning (ML) have shown promise in improving prediction accuracy [6], helping to mitigate variability and support integration into energy grids. Recently, Deep Learning (DL) techniques have gained attention for their high accuracy and better generalisation across different regions [7], [8].

The DL-based solar power prediction methods have mainly used historical power data and, in some cases, weather data. For example, radiation, temperature, and rainfall are some important classical metrics used to predict solar power generation [7]. In the context of Australia, various regions involve different First Nations seasonal information that reflects the diverse ecological knowledge and cultural practices of Indigenous communities throughout the country. Incorporating First Nations seasonal knowledge into solar power generation predictions can significantly enhance accuracy by aligning forecasts with natural cycles that have been observed and understood for thousands of years. Unlike conventional calendar systems, these seasonal insights are deeply rooted in local ecological cues, such as plant and animal behaviours, which are closely tied to changes in sunlight and weather patterns. By integrating this knowledge, predictions can be tailored to reflect more granular shifts in environmental conditions, leading to more precise and culturally informed forecasting for specific regions across Australia.

Australian First Nations or Aboriginal people are the original custodians of the land, with diverse cultures and knowledge systems that have been sustained for over 60,000 years [9]. Notably, with Australia's strong solar potential, there's increasing focus on using renewable energy to support First Nations people, backed by new funding for sustainable energy projects.[1] Additionally, First Nation communities in northern and central Australia possess seasonal calendars that are specific to their local community. Tiwi, Gulumoerrgin, Kunwinjku, and Ngurrungurrudjba are among the most widely used calendars by First Nation peoples in the northern regions of Australia. Traditional Owners from the Tiwi Islands and the Tiwi Land Council created the Tiwi Calendar, which includes three seasons reflecting their ecological knowledge. The Gulumoerrgin community in Darwin recognises seven main seasons. Traditional Owners from Kunbarlanja (Gunbalanya) developed the Kunwinjku calendar based on their seasonal and environmental knowledge, while the Ngurrungurrudjba calendar, created by Traditional Owners from the Yellow Water region, reflects their Kundjeyhmi knowledge of seasons and the environment. These calendars are closely tied to weather patterns and seasons. The deep understanding of local climate in these calendars enables First Nations people to make informed resource management and sustainability decisions. As climate change affects weather patterns, knowledge of these calendars becomes crucial for adapting to environmental challenges.

Incorporating First Nations seasonal cycles into solar power forecasting is valuable, particularly as solar energy will increasingly be supplied to rural communities in Australia. This approach aligns with the culturally ingrained calendar interpretations of these communities, including First Nations people. However, to the best of our knowledge, no existing work incorporates this seasonal information to predict solar power generation effectively. Furthermore, standalone DL models are prone to errors, as individual models are not robust to noise and outliers, which is a common case in solar power data. Considering these challenges, in this article, a novel set of metrics are introduced along with an ensemble DL approach to perform solar power prediction. The key contributions of this article are summarized as follows.

1) A set of novel metrics, namely *First Nations Seasonal Metrics (FNS-Metrics)*, has been created based on First Nations seasonal information, which includes the First Nations seasonal information from calendars such as Tiwi, Gulumoerrgin, Kunwinjku, Ngurrungurrudjba and the modern calendar known as Red Centre.
2) A novel framework consisting of three 1-dimensional convolutional (Conv1D) layers and an ensemble of a Transformer model and a long short-term memory (LSTM) model, as given in Fig. 1, is proposed to predict solar power generation accurately. This approach employs a weighted late fusion of the features for optimal performance.
3) A new dataset, namely AliDKA,[2] is constructed from data collected at the Desert Knowledge Australia (DKA) Solar Centre in Alice Springs for the purpose of accurate solar power prediction. This is the first solar power dataset to incorporate First Nations seasonal information for solar power prediction. The results obtained for the proposed approach on this dataset demonstrate that it outperforms existing methods in solar power prediction.

Section II provides a comprehensive analysis of related work in power prediction. The novel metric and proposed power prediction framework are thoroughly described in Section III. Section IV presents the experimental results and performance evaluations. Lastly, Section VI offers conclusions and suggestions for future research.

II. RELATED WORKS

There have been numerous research works on solar power prediction, with the majority of these studies utilising DL techniques [10]. To support the development of these kinds of automated solar power prediction methods, recently, many datasets have also been introduced [11]. Recent advances in DL have led to more accurate predictions of solar power generation [12].

In [13], a regression technique is proposed to automatically forecast solar power generation. Further, the novel loss function proposed in their approach enhances the performance of ML models. Yet, the performance of these ML models does not meet the expected level. On the other hand, the Convolutional Neural Network (CNN) has shown strong performance in forecasting solar power generation [14]. A key contribution of this study is a common model framework with a classification module that increases adaptability and generalisation

[1] https://www.energy.gov.au/news-media/news/new-funding-renewable-energy-first-nations-communities [last accessed: 29 August 2024]

[2] This dataset will be made available after acceptance.

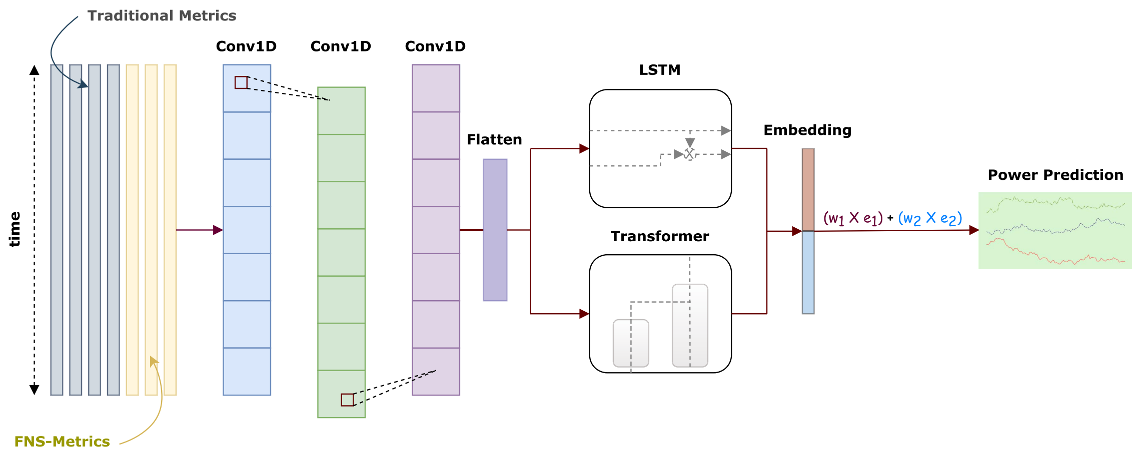

FIGURE 1. **The proposed ensemble model with three Conv1D layers and the ensemble of the LSTM model and the Transformer model. The traditional and FNS-Metrics are inputted for power prediction.**

to predict known and unknown sites under various environmental conditions. Hamad et al. [4] proposed DSCLANet, a dual-stream CNN-LSTM, followed by a self-attention mechanism. The DSCLANet achieved the MSE, MAE and RMSE of 0.0173, 0.0667 and 0.1273, respectively. In [15], an efficient short-term forecasting model for solar power production was proposed using a Variational Auto-Encoder (VAE) that demonstrates low error rates. In all these works, solar power is predicted, whereas, in a very recent work, data gathered from a wind–solar tower system were used, and deep neural networks were proposed [16]. In [17], a comparative study of six machine learning techniques is conducted, with all six demonstrating comparable performance in solar power prediction.

Transfer learning with deep neural networks is highly effective for short-term prediction of solar power [18]. The LSTM model with transfer significantly improves prediction accuracy compared to the new LSTM model using the inadequate dataset. Elsaraiti et al. [19] proposed an LSTM-based solar power prediction approach that outperformed the multi-layer perceptron (MLP). In [20], the bidirectional LSTM (BiLSTM) model and the extreme learning machine (ELM) algorithm are used to effectively predict solar power. In this study, the improved ELM serves as the primary prediction model. Kim et al. [21] proposed a two-step model for predicting solar power generation, which utilises weather information by connecting unannounced weather variables with announced weather forecasts in a sequential modelling process. Mo et al. [22] proposed a novel multi-step solar prediction (MSSP) model developed with a transformer network for solar power prediction, which demonstrated very good performance [22]. In [23], a comprehensive analysis of some state-of-the-art DL models is performed. The authors compared MLP, LSTM, and gated recurrent unit (GRU) techniques, finding that MLP is the most efficient model, while GRU demonstrated higher speed than LSTM despite having more layers. Zhu et al. [24] proposed the SL-Transformer for time-series power forecasting in wind and solar energy, achieving an R^2 of 0.9989.

In summary, most of the existing power prediction approaches are limited in performance. Unlike individual model-based approaches, ensemble learning methods have demonstrated promising results in recent years [25]. For example, in [7] and [26], deep ensemble approaches demonstrated superior performance in predicting solar power. Taking these into consideration, our approach utilises a novel ensembling of Transformer and LSTM models, enhanced by convolutional preliminary layers to improve the performance. In addition, none of these approaches have incorporated factors derived from various First Nations calendars and their corresponding seasonal cycles.

III. PROPOSED METHOD

In this section, the proposed FNS-Metrics and the novel power prediction framework are explained in detail. The FNS-Metrics are designed to incorporate various Australian First Nations seasonal cycles, providing a culturally informed approach to evaluating solar power generation. The novel power prediction framework integrates three Conv1D layers with an ensemble of Transformer and LSTM models.

A. FNS-METRICS

Traditionally, solar power prediction is based on historical data and weather data. Some of these approaches take advantage of past solar irradiance and meteorological conditions to model and forecast power output. In contrast, in the proposed work, the First Nations seasonal information taken from four calendars, such as *Tiwi*, *Gulumoerrgin (Larrakia)*, *Kunwinjku*, *Ngurrungurrudjba* and a modern *Red Centre* calendar, is used to create the FNS-Metrics. While other First Nations calendars are available, they often feature numerous seasons with fluid boundaries and significant overlaps, making them less suitable for precise solar power forecasting. By incorporating the seasonal information from four major First Nations calendars

TABLE 1. Formulation of the FNS-Metrics Using the Season Information Taken From *Tiwi*, *Gulumoerrgin (Larrakia)*, *Kunwinjku*, *Ngurrungurrudjba*, and *Red Centre* Calendars. Here, **s** and **u** Represent Singleton and Union Variables, Respectively, Where **s** Represents the Variables for the Single-Season Information, and **u** Represents the Variables for the Information of Overlapping Seasons

Months	Tiwi	Gulumoerrgin	Kunwinjku	Ngurrungurrudjba	Red Centre
January	$T_{s,3}$	$G_{s,1}$	$K_{s,1}$	$N_{s,1}$	$R_{s,1}$
February	$T_{s,3}$	$G_{s,1}$	$K_{s,1}$	$N_{s,1}$	$R_{s,1}$
March	$T_{s,1}$	$G_{u,2}$	$K_{u,2}$	$N_{s,1}$	$R_{s,2}$
April	$T_{s,1}$	$G_{u,3}$	$K_{s,3}$	$N_{s,2}$	$R_{s,2}$
May	$T_{s,1}$	$G_{s,4}$	$K_{s,4}$	$N_{s,3}$	$R_{s,2}$
June	$T_{s,1}$	$G_{u,5}$	$K_{u,5}$	$N_{u,4}$	$R_{s,3}$
July	$T_{s,1}$	$G_{u,6}$	$K_{s,6}$	$N_{s,5}$	$R_{s,3}$
August	$T_{s,1}$	$G_{u,6}$	$K_{u,7}$	$N_{u,6}$	$R_{s,3}$
September	$T_{s,2}$	$G_{u,7}$	$K_{s,8}$	$N_{s,7}$	$R_{s,4}$
October	$T_{s,2}$	$G_{s,8}$	$K_{u,9}$	$N_{u,8}$	$R_{s,4}$
November	$T_{s,2}$	$G_{u,9}$	$K_{s,10}$	$N_{s,9}$	$R_{s,4}$
December	$T_{s,3}$	$G_{u,9}$	$K_{s,10}$	$N_{s,9}$	$R_{s,1}$
Variables	**3**	**9**	**10**	**9**	**4**

and one modern calendar, the FNS-Metrics aims to precisely capture weather conditions, encompassing not only temperature, irradiance and rainfall but also the nuanced details of transitional weather patterns that are crucial for solar power forecasting.

Table 1 presents the formulation of FNS-Metrics based on seasonal information from four First Nations calendars and one modern calendar. Each row corresponds to a month of the year, with the columns representing the seasons associated with each region. The notations **s** and **u** are used to differentiate between singleton and union variables, respectively. The singleton variables (**s**) correspond to months that fall strictly within a single season, while the union variables (**u**) indicate months that overlap between two seasons. For example, in March, the Tiwi region is in a distinct single season denoted by $T_{s,1}$, while in the Gulumoerrgin and Kunwinjku regions, the same month spans multiple seasons, represented by $G_{u,2}$ and $K_{u,2}$, respectively. By explicitly encoding overlapping seasons using union variables, the model is better equipped to represent transitional weather patterns that impact solar power generation. Furthermore, this formulation facilitates the incorporation of region-specific First Nation knowledge systems, which define seasonal boundaries based on ecological indicators rather than rigid calendar structures.

Based on the seasons extracted from the *Tiwi*, *Gulumoerrgin (Larrakia)*, *Kunwinjku*, *Ngurrungurrudjba*, and *Red Centre* calendars, five additional features are constructed. These features potentially represent diverse First Nations seasonal patterns and consist of 3, 9, 10, 9, and 4 possible categories, respectively.

B. CONV-ENSEMBLE FRAMEWORK

As shown in Fig. 1, the proposed framework consists of three Conv1D layers to extract high-level features. Conv1D is used because it is effective for extracting high-level features in sequential data, such as time series or text, due to its ability to capture local features, enable hierarchical feature learning, and maintain translation invariance [27]. In solar power prediction, capturing temporal dependencies and short-term fluctuations is essential for accurate forecasting, and Conv1D effectively models these patterns. Each layer extracts progressively abstract temporal features, enabling both fine- and coarse-grained representation learning. Moreover, Conv1D offers computational efficiency due to its reduced parameter count compared to recurrent architectures, making it suitable for real-time applications. All three Conv1D layers utilise the rectified linear unit (ReLU) as their activation function. The output features from the third Conv1D layer are then fed into a flatten layer to convert the multi-dimensional feature map into a one-dimensional vector. Let the input feature be represented by $\mathbf{x} \in \mathbb{R}^{L\times C}$, the output after the first Conv1D layer can be expressed as follows based on the definition provided in [28]:

$$\mathbf{h}_1 = \mathrm{ReLU}(\mathbf{W}_1 * \mathbf{x} + \mathbf{b}_1) \tag{1}$$

where, $\mathbf{W}_1 \in \mathbb{R}^{k_1\times C\times M_1}$ is the filter of the first Conv1D layer, with k_1 being the kernel size, C the number of input channels and M_1 the number of output channels. $\mathbf{b}_1 \in \mathbb{R}^{M_1}$ is the bias term. $*$ denotes the convolution operation across the time dimension.

The output after the first Conv1D layer, $\mathbf{h}_1$, is then fed into the second Conv1D layer. Similarly, the output from the second Conv1D layer is passed to the third Conv1D layer for further processing. A flatten layer is then used to convert the multi-dimensional feature map into a one-dimensional vector. The output of the flatten layer can be represented as follows based on the definition provided in [29]:

$$\mathbf{z} = \mathrm{Flatten}(\mathbf{h}_3) \tag{2}$$

where, $\mathbf{z} \in \mathbb{R}^{L'\times M_3}$ is the output after the flatten layer, with L' being the reduced length of the time series after convolution, flattening it into a vector of size $L' \times M_3$. $\mathbf{h}_3$ is the output feature of the third Conv1D layer.

TABLE 2. Layer Details of the Transformer Model in the Proposed Conv-Ensemble Framework

Layer #	Layer Type	Input Shape	Output Shape
1	Input	$[N,]$	$[N,]$
2	Multi-Head Attention	$[N,]$	$[N,64]$
3	Dropout	$[N,64]$	$[N,64]$
4	Layer Normalization	$[N,64]$	$[N,64]$
5	Dense	$[N,64]$	$[N,64]$
6	Dropout	$[N,64]$	$[N,64]$
7	Layer Normalization	$[N,64]$	$[N,64]$
8	Dense	$[N,64]$	$[N,]$

TABLE 3. Layer Details of the LSTM Model in the Proposed Conv-Ensemble Framework

Layer #	Layer Type	Input Shape	Output Shape
1	Input	$[N,]$	$[N,]$
2	LSTM	$[N,]$	$[N,64]$
3	Dropout	$[N,64]$	$[N,64]$
4	LSTM	$[N,64]$	$[64,]$

1) ENSEMBLE MODEL

In the proposed framework, an ensemble of a transformer and an LSTM model is used. The transformer network is efficient in time series analysis, which arises from its ability to capture long-range dependencies and intricate temporal patterns through self-attention mechanisms [30]. Consider that $\mathbf{z}$ is in the shape of $[N,]$, Table 2 shows the organisation of the layer with the corresponding input and output shapes. The output shape of the feature is again $[N,]$, which is a 1-dimensional vector. The proposed transformer model consists of eight layers, one of which is a multi-head attention layer. This layer is used to capture diverse relational dynamics between input elements that allow the model to attend to multiple aspects of the input sequence concurrently throughout its other layers.

Subsequently, an LSTM model is incorporated into the ensemble framework. In general, similar to transformers, LSTMs are also suitable for time series analysis due to their ability to effectively capture and maintain long-term dependencies in sequential data through their memory cell structure [31]. The input for the LSTM model is the same as for the transformer, with $\mathbf{z}$ having a shape of $[N,]$. Table 3 gives the layer information for the LSTM model integrated in the proposed Conv-Ensemble approach. The model consists of two LSTM layers and one dropout layer, with the final output shape of the LSTM model being [64,].

As illustrated, the flattened feature $\mathbf{z}$ is then fed into the ensemble model, where it is processed separately by both the transformer and the LSTM models. Assume that the output features of the transformer model and the LSTM model are $\mathbf{e}_1$ and $\mathbf{e}_2$, respectively. A weighted concatenation of the output features $\mathbf{e}_1$ and $\mathbf{e}_2$ is performed to combine the features, as given below.

$$\mathbf{e}_{final} = \mathbf{w}_1 \times \mathbf{e}_1 + \mathbf{w}_2 \times \mathbf{e}_2 \tag{3}$$

where, $\mathbf{w}_1$ and $\mathbf{w}_2$ are the weights given for the features extracted by the transformer and the LSTM models, respectively.

These weights are optimised through a grid search mechanism during the validation process to ensure the most effective feature integration. Specifically, the grid search iteratively evaluates a predefined set of weight combinations where $w_1 + w_2 = 1$, such as $(0.1, 0.9), (0.2, 0.8), \ldots, (0.9, 0.1)$, to identify the pair that yields the best validation performance. By systematically scanning this constrained search space, the model can balance the contribution of both features $\mathbf{e}_1$ and $\mathbf{e}_2$ in a controlled manner. The optimal weights are selected based on the performance metric MSE, calculated on the validation set. The resultant feature, derived from this weighted combination, is subsequently utilised to predict solar power generation.

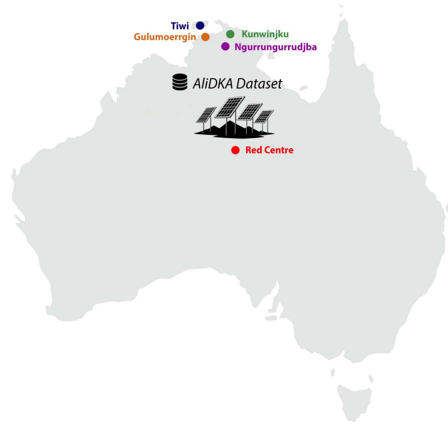

FIGURE 2. AliDKA dataset construction: Location of the solar farm and calendars considered.

IV. EXPERIMENTS

In this section, the details of the newly constructed AliDKA dataset details, implementation and protocols and the experimental results for the proposed novel FNS-Metrics and the Conv-Ensemble framework are discussed.

A. ALIDKA DATASET

The solar power data in the newly constructed AliDKA Dataset is sourced from the Desert Knowledge Australia Solar Centre.[3] Fig. 2 shows the location of the solar farm where the AliDKA dataset was collected, along with the First Nation calendars and the Red Centre calendar considered in this work. These First Nations calendars align closely with the seasonal and environmental patterns observed in the solar farm area, offering a more region-specific understanding of climate variations. Although the solar farm is outside the region where these Indigenous seasonal calendars originated,

[3]https://dkasolarcentre.com.au/download?location=alice-springs

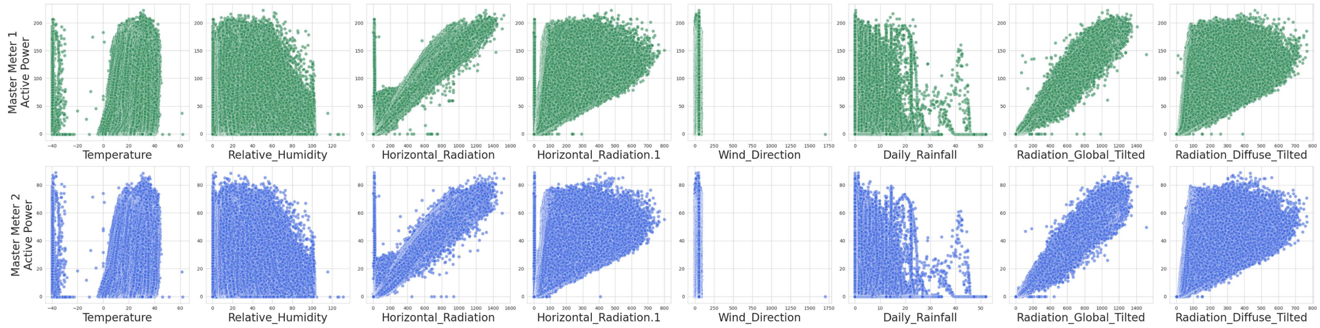

FIGURE 3. **Correlation of traditional features with both active power readings taken in power meter 1 and power meter 2, individually.**

their use is justified by geographical similarities and proven broader applicability in comparable contexts.[4] Further, their detailed reflection of local and surrounding weather conditions provides valuable insight that improves the accuracy of solar power generation predictions in this region.

Launched in 2008 in Alice Springs, this solar facility is the world's largest multi-technology solar demonstration site. Its extensive array of solar technologies allows for comprehensive data collection and analysis across various solar energy systems. Located in Alice Springs, Australia, the Desert Knowledge Australia Solar Centre is significantly influenced by First Nations seasonal information, given that the majority of Australia's First Nations communities reside in the Red Centre and northern regions [32]. Although the Red Center calendar closely aligns with the region where the AliDKA dataset is collected, nearby Indigenous calendars may also have a significant influence due to their proximity. This influence is reflected in the dataset, which incorporates seasonal patterns and environmental factors specific to these indigenous communities, thereby enhancing the relevance and accuracy of the solar power data for local and regional applications. The integration of First Nations seasonal knowledge underscores the commitment to incorporating traditional ecological insights into modern technological frameworks.

The solar power data in the AliDKA Dataset, collected from 2019 to 2024, consists of data points recorded at five-minute intervals. Altogether, the final cleaned AldKa dataset comprises 465,078 rows of recordings, which provides a substantial foundation for analysing solar power generation patterns. Further, collected over a period of five years, the dataset captures a diverse range of weather patterns, seasonal variations, and rare environmental conditions, all of which critically influence solar power generation. Historical data before 2019 are excluded from the AliDKA Dataset to ensure consistency and relevance, as the dataset focuses on the most recent technological advancements and weather conditions relevant to recent years. In addition to the five features provided by the novel FNS-Metrics, the AliDKA Dataset includes eight traditional features, such as temperature, relative humidity, two readings for horizontal radiation, wind direction, daily rainfall, and both global and diffuse tilted radiation—that exhibit a high correlation with the active power generated by solar cells.

According to the literature, these traditional features are proven to be significant in predicting solar power [10]. In addition, the impact of these features is examined and validated through further correlation analysis. Fig. 3 presents the correlation between eight traditional features and the two active power measurements read on master meters 1 and 2, analysed individually. Although each traditional feature is examined for its relationship with active power readings from both meters to understand how various meteorological factors influence solar power generation, the influence of individual features is not analysed in this study, as the primary focus is on investigating the impact of the proposed novel FNS-Metrics.

B. IMPLEMENTATION AND PROTOCOLS

The Conv-Ensemble framework is implemented in Python using the TensorFlow[5] ML framework due to its flexibility and wide support for deep learning models. Training on an NVIDIA GeForce GTX 1080 Titan GPU server ensures efficient handling of computationally intensive operations, significantly reducing training time. The dataset is split with 80% allocated for training and 20% for testing. The test set consists entirely of unseen data, which ensures a clear separation from the training process. This setup allows us to rigorously evaluate the model's ability to generalise to out-of-distribution (OOD) scenarios as well. The model was trained for 50 epochs using the Adam optimiser with mean squared error (MSE) as the loss function, incorporating early stopping to prevent overfitting. The transformer model is configured with hyperparameters that include 4 attention heads, a key dimension of 64, a dropout rate of 0.1, an epsilon value of 1e-6, and ReLU as the activation function. The LSTM model is configured with 64 units and a dropout rate of 0.1.

The results are presented using evaluation metrics, such as the coefficient of determination R-Squared ($\mathbf{R^2}$) and MSE. The $\mathbf{R^2}$, as shown in (4), serves as a performance indicator to evaluate how effectively a model captures the underlying patterns in the data. The values for $\mathbf{R^2}$ range between 0 and 1, where a high value does not always imply that the model is

[4] [Online]. Available: https://www.csiro.au/en/research/indigenous-science/indigenous-knowledge/calendars

[5] [Online]. Available: https://www.tensorflow.org/

TABLE 4. Comparison of the Results Obtained on the AliDKA Dataset for Solar Power Prediction of the Active Power Data From Power Meter 1. Trad - Traditional Metrics, RC - Red Centre and FNS - FNS-Metrics. The Models Highlighted in Bold Represent Different Configurations Used for the Ablative Study

Models	R^2			MSE		
	Trad	Trad + RC	Trad + FNS	Trad	Trad + RC	Trad + FNS
GAM [17]	0.3565	0.3592	0.3811	190.17	188.62	181.54
SL-Transformer [24]	0.4274	0.4303	0.4963	160.55	159.43	152.48
BiLSTM [20]	0.3908	0.4005	0.4199	179.62	177.51	171.74
DSCLANet [4]	0.4470	0.4476	0.5136	154.63	152.18	147.31
LSTM	**0.3715**	**0.3789**	**0.4013**	**184.31**	**183.17**	**178.22**
Transformer	**0.4023**	**0.4138**	**0.4517**	**168.62**	**166.57**	**160.74**
Conv-LSTM	**0.4914**	**0.5128**	**0.5891**	**136.63**	**132.52**	**124.12**
Conv-Transformer	**0.5852**	**0.6137**	**0.6792**	**122.15**	**119.57**	**110.08**
Conv-Ensemble	**0.7125**	**0.7347**	**0.8015**	**101.26**	**100.87**	**96.13**

good, especially if the model is overfitting.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{4}$$

where, y_i represents the observed values, $\hat{y}_i$ the predicted values, and $\bar{y}$ the mean of the observed values. The numerator, $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$, measures the sum of squared residuals, indicating model errors, while the denominator, $\sum_{i=1}^{n}(y_i - \bar{y})^2$, measures the total variance in the observed data.

The values for $\mathbf{R^2}$ range between 0 and 1, where a high value does not always imply that the model is good, especially if the model is overfitting. Hence, the MSE, as given in (5), is also used as an evaluation metric along with $\mathbf{R^2}$.

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{5}$$

In this equation, y_i represents the observed values, $\hat{y}_i$ the predicted values, and n the total number of data points.

C. RESULTS AND DISCUSSION

The proposed Conv-Ensemble framework is evaluated using the newly constructed AliDKA dataset, and the results are subsequently compared with existing approaches and baselines. Some of the existing approaches have been reproduced based on the details provided in the original articles, with potential slight variations in the implementation. The baselines compared are variations of the proposed approach that do not integrate the ensemble methodology, as given below.

1) *Conv-Transformer:* This configuration is derived by detaching the LSTM component from the proposed Conv-Ensemble framework and eliminating the weighted concatenation of embeddings.
2) *Conv-LSTM:* This is constructed by detaching the Transformer component from the proposed Conv-Ensemble framework, with the weighted concatenation of embeddings also removed, as no ensemble is involved.
3) *Transformer and LSTM:* These models are composed solely of the Transformer and LSTM components utilised in the proposed method, with no concatenation employed, as they are treated as individual models.

A comparative analysis with these baseline models helps demonstrate the superiority of the ensemble architecture inherent in the proposed Conv-Ensemble framework. Furthermore, the impact of each calendar's information incorporated into the FNS-metrics is systematically evaluated by testing the proposed approach and baselines individually for each calendar using traditional metrics.

Tables 4 and 5 present the results obtained for the proposed framework, as well as for other baseline and state-of-the-art methods in solar power prediction of the active power data from Power Meter 1 and Power Meter 2, respectively. The state-of-the-art approaches include generalised additive model (GAM) [17], Savitzky–Golay filter and local outlier filter with LSTM and transformers (SL-Transformer) [24], BiLSTM [20] and DSCLANet [4]. The $\mathbf{R^2}$ and MSE values are reported both with and without incorporating the novel FNS-Metrics features. In addition, the results are reported using Red Centre information with traditional features.

Among the models for solar power prediction of the active power data from Power Meter 1, the proposed Conv-Ensemble model with the FNS-Metrics features exhibits the best performance, achieving the highest $\mathbf{R^2}$ value of 0.8015 and the lowest MSE of 96.13. This represents an improvement of 0.0890in $\mathbf{R^2}$ and a reduction of 5.13in MSE compared to the Conv-Ensemble model used without the FNS-Metrics features. In terms of $\mathbf{R^2}$ and MSE, the Conv-Transformer and Conv-LSTM models achieved the second- and third-best performances, respectively. In predicting active power for Power Meter 1, the inclusion of Red Centre calendar information slightly improves performance compared to using only traditional features. It is also important to note that the arrangement of Conv1D layers with transformer and LSTM networks significantly enhances solar power prediction capabilities compared to standalone transformer and LSTM networks. The SL-Transformer [24] and BiLSTM [20] approaches also

TABLE 5. Comparison of the Results Obtained on the AliDKA Dataset for Solar Power Prediction of the Active Power Data From Power Meter 2. Trad - Traditional Metrics, RC - Red Centre and FNS - FNS-Metrics. The Models Highlighted in Bold Represent Different Configurations Used for the Ablative Study

Models	R^2			MSE		
	Trad	Trad + RC	Trad + FNS	Trad	Trad + RC	Trad + FNS
GAM [17]	0.3715	0.3762	0.3941	101.22	100.71	94.16
SL-Transformer [24]	0.4722	0.4891	0.5321	72.64	70.92	65.34
BiLSTM [20]	0.4213	0.4314	0.4716	88.64	86.47	81.78
CNN [33]	0.3756	0.3921	0.4178	97.18	95.38	91.33
CNN-LSTM [34]	0.4328	0.4521	0.4932	80.55	78.46	71.91
DSCLANet [4]	0.4961	0.5047	0.5524	63.42	61.51	54.52
LSTM	**0.4012**	**0.4118**	**0.4481**	**93.17**	**92.91**	**90.03**
Transformer	**0.4562**	**0.4688**	**0.5124**	**81.11**	**79.63**	**73.61**
Conv-LSTM	**0.5512**	**0.5734**	**0.6348**	**50.12**	**48.67**	**42.73**
Conv-Transformer	**0.6671**	**0.6837**	**0.7394**	**38.64**	**36.75**	**30.37**
Conv-Ensemble	**0.7645**	**0.7934**	**0.8641**	**29.16**	**27.24**	**22.41**

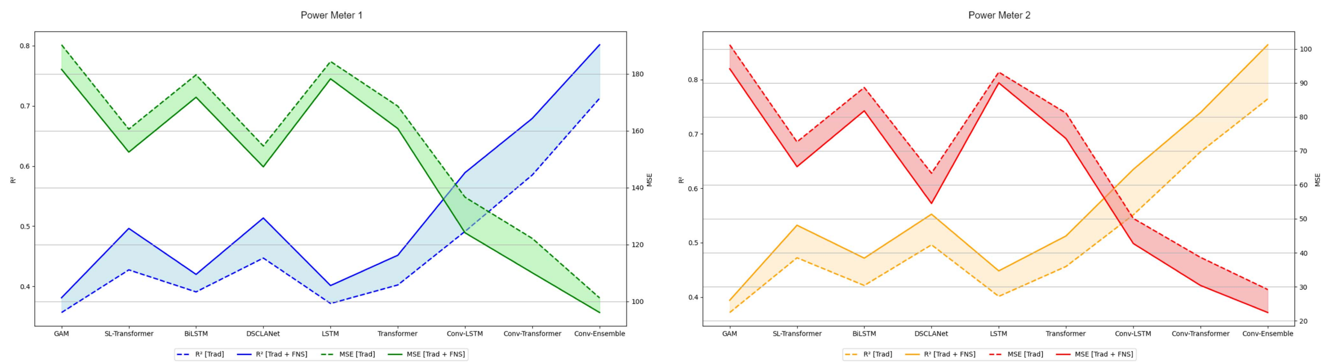

FIGURE 4. Improvements in R^2 and MSE of all models in solar power prediction with and without FNS-Metrics, for active power data from Power Meters 1 (left) and 2 (right).

demonstrated superior performance compared to their respective counterparts, the standard transformer and LSTM networks.

With the active power data from Power Meter 2, as shown in Table 5, the proposed Conv-Ensemble framework again outperforms baseline models and existing state-of-the-art methods in predicting solar power generation. Similar to the experiments conducted on the active power data of Power Meter 1, most of the experimental results and the ranking of the methods in terms of $\mathbf{R^2}$ and MSE are consistent with those observed for Power Meter 2. Similar to the previous case, the inclusion of Red Centre calendar information as an additional feature enhances performance compared to using only traditional features. However, the MSE values are comparatively lower for Power Meter 2 due to the lower generated power compared to Power Meter 1. This indicates that while the relative performance of the models remains similar, the absolute error values are reduced in scenarios with lower power generation.

In both cases (i.e., the active power data from Power Meters 1 and 2), all the models, including the proposed Conv-Ensemble framework, showed improved performance when the novel FNS-Metrics were combined with other traditional features. This underscores the benefits of incorporating the novel FNS-Metrics features extracted from First Nations calendars into the prediction models. Fig. 4 visually demonstrates the improvement achieved by integrating FNS-Metrics compared to the performance before their inclusion. The left figure illustrates the performance improvement of all models in solar power prediction using the active power data from Power Meter 1, while the right figure shows the performance enhancement of the models using the active power data from Power Meter 2. The enhanced prediction ability suggests that integrating various First Nations seasonal information can significantly refine forecasting models. Moreover, these results highlight the potential for incorporating diverse and culturally relevant data to improve the performance of predictive analytics in future energy applications.

Fig. 5 illustrates the comparison between the actual power generated and the predicted values, highlighting the performance of the proposed Conv-Ensemble model relative to the two baseline models, Conv-Transformer and Conv-LSTM.

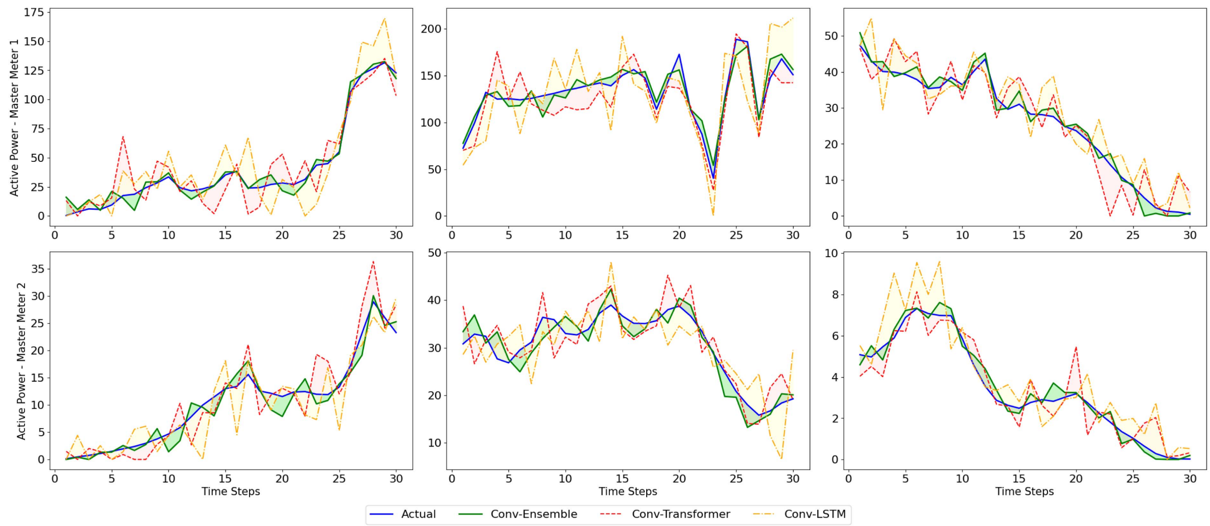

FIGURE 5. Comparison of actual and predicted solar power generation using Conv-Ensemble, Conv-Transformer and Conv-LSTM across different irradiance solar power generation windows from Master Meters 1 and 2. The power generated in both power meters is given in kWh and each time slot represents 5 minutes.

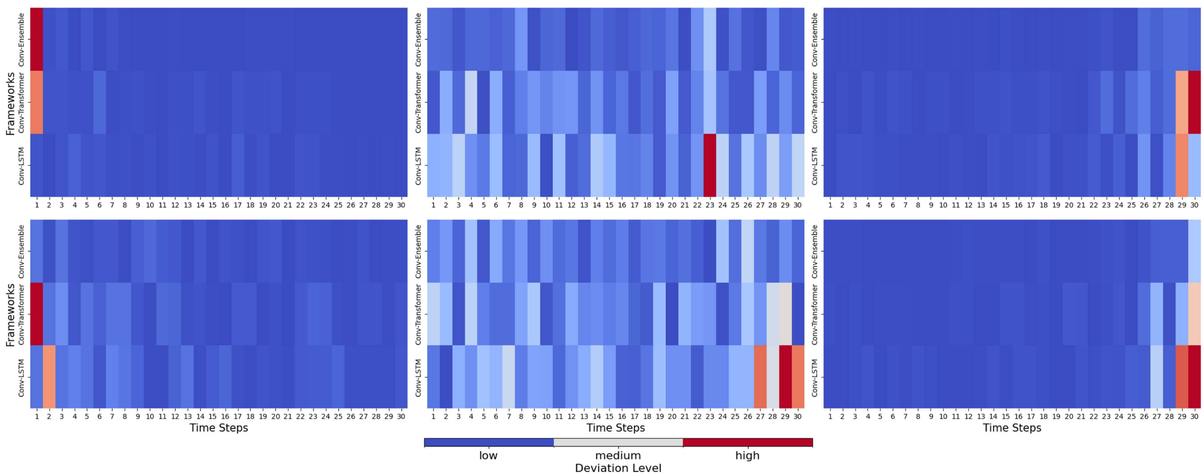

FIGURE 6. Heatmap showing error patterns in solar power generation across different irradiance periods using the proposed Conv-Ensemble approach.

Among all baselines, these two are selected because they represent the second and third best-performing approaches following the proposed framework. The top and bottom samples shown in this figure are derived from Master Meters 1 and 2, respectively. The plots on the left, middle and right correspond to solar power generation during periods of increasing irradiance (morning), peak irradiance (noon) and decreasing irradiance (afternoon), respectively. The results presented are based on the combined features from traditional metrics and FNS-Metrics. As can be seen, the proposed approach consistently outperformed others in predicting solar power across all six samples (i.e., solar power generation windows). This highlights the robustness of the proposed FNS-Metrics and the superiority of the Con-Ensemble framework in accurately predicting solar power generation.

A heatmap was generated to analyze the error patterns in solar power generation during different irradiance periods, as shown in Fig. 6. This heatmap is generated for the proposed Conv-Ensemble approach. The heatmap reveals that large errors consistently occur during peak irradiance periods when solar power generation is at its highest. These high error rates may be due to the Conv-Ensemble model's difficulty in accurately capturing the rapid fluctuations in solar power generation during these periods, leading to greater deviations between the actual and predicted values. Additionally, the increased complexity of solar dynamics at peak irradiance might challenge the ability of the proposed Conv-Ensemble model to generalise effectively. Further refinement of the model could enhance its responsiveness to these critical fluctuations, potentially improving overall predictive performance.

Notably, very high error rates are observed at the start and end of the day, corresponding to periods of low solar power generation. This pattern is visually evident in the heatmap, where red shades dominate the early morning sections of the

TABLE 6. The Result for Individual and Combined FNS-Metrics Features. Trad - Traditional Metrics

Metrics	R^2	MSE
Trad	0.7645	29.16
+ Tiwi	0.7812	28.14
+ Gulumoerrgin	0.7924	27.62
+ Kunwinjku	0.8063	26.34
+ Ngurrungurrudjba	0.8136	24.79
+ Tiwi + Gulumoerrgin	0.8194	24.05
+ Tiwi + Gulumoerrgin + Kunwinjku	0.8234	23.44
+ FNS-Metrics	**0.8641**	**22.41**

left plots and the late afternoon sections of the right plots. These high error rates may be linked to the inherent variability in solar irradiance during dawn and dusk, where the angle of the sun causes rapid changes in light intensity. Additionally, the atmospheric conditions during these times, such as increased cloud cover, can lead to unpredictable fluctuations in solar input, complicating accurate power generation, which makes the prediction inaccurate. The combination of these factors creates a challenging environment for the proposed model, highlighting the need for enhanced modelling techniques that can better account for these transient and complex conditions. Improving the model's performance during these critical periods could significantly enhance overall prediction accuracy.

To illustrate the impact of individual features incorporated in the FNS-Metrics, an ablative study is performed, and the results are summarized in Table 6. In this ablative study, only the proposed Conv-Ensemble framework is employed. First, each calendar's information is added individually to the traditional metrics, and both $\mathbf{R}^2$ and MSE are recorded. As can be seen, as features from FNS-Metrics are added, both $\mathbf{R}^2$ and MSE improve, which indicates the value of incorporating First Nation knowledge into the model. In particular, among the individual calendars, the Ngurrungurrudjba seasonal information enhanced the performance of the proposed Conv-Ensemble framework more than the other calendars. This improvement may be attributed to the fact that Ngurrungurrudjba is the region closest to the location where the solar data was collected. The performance of the proposed Conv-Ensemble framework, incorporating combinations of the First Nation calendars with traditional metrics, is also examined, as demonstrated in the last three rows of Table 6. The results demonstrate that the integration of combined First Nation calendar information leads to improved performance compared to the use of individual calendar information.

V. DISCUSSION

The proposed Conv-Ensemble framework exhibits certain limitations concerning real-time prediction capabilities. Due to the relatively long training time required, integrating recent data into the model is constrained to periodic retraining processes. This temporal lag may hinder the framework's responsiveness to abrupt changes in data distribution. Nevertheless, as a lightweight approach, the framework demonstrates faster processing compared to deeper and more complex architectures. To enhance adaptability and reduce retraining overhead, integrating incremental learning strategies could be a promising direction for future development [35].

In the past, heuristic, metaheuristic and optimisation algorithms have been employed in time series forecasting. In data-scarce scenarios, these methods are favoured for their low data requirements and computational efficiency and are often used for parameter tuning or as components in hybrid models. However, the comparison of these approaches is avoided because they generally struggle to model complex temporal dependencies and interactions across multiple variables [36]. While heuristic, metaheuristic and optimisation algorithms remain useful in specific contexts, this study focuses on deep learning due to its superior predictive accuracy and scalability. Future work may investigate hybrid frameworks that integrate the strengths of both approaches.

The computational complexity of deep neural networks, including the proposed Conv-Ensemble framework, is influenced by several key architectural and operational factors. These include the number of layers in the network, the dimensionality of the input data, and the specific operations performed within convolutional and dense (fully connected) layers. Among these, convolutional layers typically dominate the computational cost, especially in vision-based or spatial-temporal tasks. The computational complexity of a convolutional layer can be approximated as $\mathcal{O}(n \cdot k^2 \cdot m)$, where n represents the number of input feature maps, k is the spatial size of the kernel (assuming square kernels), and m denotes the number of output feature maps or filters [37]. This formulation highlights how increasing the number of filters or kernel size can significantly impact the overall computational load. While such architectures can be computationally intensive, they scale effectively on modern GPUs and are supported by optimised libraries such as TensorFlow [38], which enables practical deployment even on moderately powered hardware.

VI. CONCLUSION

In this article a novel feature set, namely FNS-Metrics for solar power generation prediction, is proposed. The FNS-Metrics uniquely incorporate the First Nations' seasonal cycles from four First Nations calendars, which is a critical consideration for accurate predictions in the top-end of Australia. Furthermore, a novel Conv-Ensemble framework is proposed, which combines Conv1D layers with transformer and LSTM networks to demonstrate the advantages of leveraging diverse feature extraction capabilities. The weighted feature concatenation technique integrated with the proposed approach further enhances the model's ability to accurately predict solar power generation. The experimental results on a newly constructed dataset from the Desert Knowledge Australia Solar Center in Alice Springs, namely the AliDKA dataset, validated the superiority of the proposed

FNS-Metrics and Conv-Ensemble framework in solar power prediction. Specifically, the Conv-Ensemble framework with FNS-Metrics consistently outperforms traditional methods, achieving state-of-the-art performance with an R^2 of 0.8641 and an MSE of 22.41. The success of the proposed approach suggests that it could be a valuable tool for advancing solar power generation prediction in rural areas like Alice Springs, Australia, by integrating the seasonal cycles of First Nations for improved accuracy and performance. In future work, the applications of the FNS-Metrics and Conv-Ensemble framework to other regions and renewable energy sources by further refine the models to enhance their generalizability. In addition, improving modelling techniques to address the higher error rates observed during periods of rapid changes in solar irradiance is essential for accurate solar power prediction.

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