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Artificial Neural Network in Fibre-Reinforced Polymer Composites using ARAS method

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Abstract

Fibre-reinforced polymer composites (FRPCs) have garnered considerable interest across industries owing to their lightweight characteristics, impressive strength-to-weight ratio, and resistance to corrosion. The performance of FRPCs is intricately tied to numerous factors encompassing fibre alignment, resin attributes, manufacturing intricacies, and ambient conditions. Accurate prediction of FRPCs' mechanical properties and behavior is pivotal for their effective design and utilization. Artificial Neural Networks (ANNs) have emerged as robust instruments for predictive modeling within materials science and engineering domains. This paper conducts an exhaustive review of ANNs' application in forecasting the mechanical attributes and conduct of FRPCs. It delves into the architecture of ANNs, prevalent neural network variants, methodologies for data preprocessing, and training algorithms. Moreover, it scrutinizes diverse research endeavors where ANNs have been harnessed to anticipate properties like tensile strength, flexural modulus, impact resistance, and fatigue endurance of FRPCs. Additionally, the paper underscores the merits and constraints associated with ANNs vis-à-vis conventional analytical and empirical models. Lastly, it outlines future avenues for research and potential advancements in ANNs' deployment for predictive modelling of FRPCs. The efficacy of ANN models in predicting the mechanical behaviour of FRPCs hinges on several critical factors, including data pre-processing techniques and training algorithms. Data pre-processing involves tasks like normalization, feature scaling, and dimensionality reduction, which enhance the efficiency and accuracy of ANN models by ensuring that input data are appropriately formatted and ranged. Training algorithms, such as backpropagation and gradient descent, iteratively adjust the weights of connections between neurons, minimizing the error between predicted and actual outcomes during the training phase.The ARAS (Analytical Hierarchy Process (AHP) and Remote Sensing) methodology represents an innovative approach that merges the principles of AHP with remote sensing techniques to streamline decision-making processes across diverse domains. This methodology capitalizes on the strengths of both AHP, which furnishes a systematic framework for multi-criteria decision-making, and remote sensing, which furnishes valuable spatial insights from satellite or aerial imagery.Model Robustness Across Datasets, Error Distribution Analysis, Prediction Confidence Intervals, Temporal Stability, Sensitivity to Hyper parameters and Transfer Learning Potential. Prediction Accuracy, Generalization Ability, Computational Efficiency, Robustness to Noise and Uncertainty, Interpretability and Feature Importance Analysis. the Rank in Role of AI in Artificial Neural Network in Fibre-Reinforced Polymer Composites using ARAS Method Transfer Learning Potential is showing the highest value and Temporal Stability is showing the lowest value.

Keywords: Model Robustness Across Datasets, Error Distribution Analysis, Prediction Confidence Intervals, Temporal Stability, Sensitivity to Hyper parameters and Transfer Learning Potential

Introduction

Artificial Neural Networks (ANNs) have emerged as potent tools for predictive modelling in the domain of fibre-reinforced polymer composites (FRPCs). FRPCs, renowned for their blend of robustness, lightness, and resistance to corrosion, find increasing use across diverse sectors like aerospace, automotive, and construction. Given the intricate interplay between FRPCs' mechanical traits and factors such as fibre alignment, resin properties, manufacturing intricacies, and environmental variables, precise predictive models are essential for effective design and optimization. ANNs, drawing inspiration from the intricate neural networks in the human brain, offer a promising avenue for capturing the complex, non-linear relationships inherent in FRPCs [1]. At the heart of ANNs lies a network of interconnected artificial neurons organized into layers. These neurons receive input signals, apply weights to them, and generate an output signal via an activation function. The architecture of ANNs can vary greatly, ranging from straightforward feedforward networks to more intricate recurrent or convolutional networks, depending on the problem at hand. In the realm of FRPCs, feedforward networks are commonly employed to forecast mechanical properties such as tensile strength, flexural modulus, impact resistance, and fatigue life [2]. The efficacy of ANN models in predicting the mechanical behavior of FRPCs hinges on several critical factors, including data preprocessing techniques and training algorithms. Data preprocessing involves tasks like normalization, feature scaling, and dimensionality reduction, which enhance the efficiency and accuracy of ANN models by ensuring that input data are appropriately formatted and ranged. Training algorithms, such as backpropagation and gradient descent, iteratively adjust the weights of connections between neurons, minimizing the error between predicted and actual outcomes during the training phase [3]. Several studies have showcased the effectiveness of ANNs in forecasting various mechanical properties of FRPCs. For instance, ANNs have been utilized to simulate the tensile behavior of FRPCs under diverse loading conditions, accounting for variables like fibre volume fraction, orientation, and matrix properties. Similarly, ANN models have been developed to predict the flexural modulus of FRPCs based on factors such as fibre type, stacking sequence, and curing temperature. Moreover, ANNs hold promise in estimating impact strength and fatigue life, crucial for assessing the durability and reliability of FRPC components in real-world scenarios [4].However, ANNs also present challenges in the context of FRPC modeling. One such challenge is the necessity for large amounts of high-quality training data, which can be expensive and time-consuming to acquire, especially for specialized FRPC formulations or intricate loading conditions. Additionally, overfitting—a phenomenon where the model performs well on training data but fails to generalize to unseen data—remains a concern, necessitating meticulous regularization techniques and model validation procedures [5].Fibre-reinforced polymer composites (FRPCs) have become essential materials across various industries due to their lightweight properties, high strength-to-weight ratio, resistance to corrosion, and flexibility in design. Consisting of a polymer matrix reinforced with high-performance fibres like carbon, glass, or aramid, FRPCs present a compelling alternative to conventional materials in aerospace, automotive, marine, and civil engineering sectors. However, achieving optimal design, performance, and manufacturing processes for FRPCs requires a thorough comprehension of their intricate mechanical, thermal, and structural characteristics. In recent times, Artificial Neural Networks (ANNs) have emerged as prominent contenders for transforming FRPC research and development [6]. Inspired by the neural networks found in the human brain, ANNs possess the capability to learn from data, detect patterns, and generate predictions without explicit programming. This inherent adaptability makes ANNs invaluable tools for modeling, forecasting, and refining the properties and functionality of FRPCs, thus expediting the material design and innovation cycle. This introduction seeks to delve into the burgeoning utilization of Artificial Neural Networks within the domain of FRPCs, elucidating their diverse advantages and tackling relevant research trends and obstacles. By synthesizing insights from seminal literature, this discussion will underscore the broad spectrum of ANNs' applications in FRPC research, underscoring their pivotal role in propelling the advancement of lightweight, high-performance composite materials for a wide array of industrial applications [7]. Artificial Neural Networks (ANNs) replicate the structure of biological nervous systems by simulating microstructures akin to neurons. ANNs, as computational systems, mimic the basic components and organization of the brain, borrowing terminology from neuroscience textbooks. Understanding the natural nervous system entails grasping the fundamental role of the human brain—an organ composed of specialized cells responsible for actions and influenced by past experiences, enabling thinking and application of skills [8]. Neurons, the core units, possess the remarkable ability to form connections with up to 200,000 other neurons, facilitating the brain's computational power through intricate networks. Each biological neuron comprises dendrites, soma, axons, and synapses, which collectively process input, perform non-linear functions, and produce output. Constructed in a three-dimensional manner from microscopic elements, biological neural networks exhibit nearly limitless connectivity among neurons, fostering complex information processing capabilities [9]. Polymer composites find increased utility in engineering applications, particularly where friction and wear are significant concerns. Understanding wear properties requires examining the correlation between various parameters and conditions under which these composites operate. Achieving optimal combinations of ingredients and service conditions is crucial for fulfilling diverse design requirements and addressing specific needs.Developing models based on existing experimental data is essential for predicting material properties, which not only aids in composite design but also reduces the need for extensive testing. Artificial neural networks (ANNs) have emerged as valuable tools in this endeavor. Vagvala, et al. discussed strategies for future-proofing cloud adoption, focusing on smart selection frameworks and performance optimization in dynamic business environments [10].

ANNs directly learn relationships from examples without relying on prescribed formulas, thereby offering a more flexible approach to problem-solving. During training, ANNs establish causal connections between input data and their corresponding outcomes, enabling them to efficiently analyze complex material science and engineering issues. Thus far, ANNs have demonstrated efficacy across a broad spectrum of material science and engineering domains [11]. Recent studies have extensively applied Artificial Neural Networks (ANNs) to monitor the manufacturing and mechanical behavior of fiber-reinforced composites. A comprehensive review has been conducted on the latest advancements in ANNs for various applications, including polymeric composites, polymers, metals, and other materials. Noteworthy among these is Hagelein's research, which employs ANNs in aerospace applications. This current study aims to consolidate the application of ANNs specifically for optimizing the mechanical properties of fiber-reinforced polymeric compounds [12].Training artificial neural networks (ANNs) involves utilizing historical data, including cyclic loading and homogeneous relaxation, derived from models that account for uniaxial deformation. These models characterize the physical material parameters and identify inclusive sets. Previous studies have demonstrated the effectiveness of ANNs in predicting material behavior, particularly in the case of polymeric composites like carbon-fiber reinforced epoxy. The ANN developed by al-Haykh and Karmestani in an earlier investigation employed a hierarchical feedforward architecture [13]. This ANN takes inputs such as load level and time, and outputs creep strain. Training this model involves utilizing sample data and employing optimization algorithms such as simple steep descent, which was later extended to include temperature as an additional input and other algorithms like conjugate gradient, scaled conjugate gradient, and truncated Newton methods. Evaluation of these algorithms showed that while traditional parallelism was superior, the performance of steep descent was comparatively slower. This study aims to develop a linear non-viscoelastic model using ANNs to predict stress relaxation behavior in polymer matrix composites and to compare the results. The subsequent sections of this article will detail the tests conducted for this purpose [14]. Fiber-reinforced polymer composites (FRPCs) are complex materials, with various factors such as composition, material type, and manufacturing processes contributing to their complexity. These factors make them suitable for a wide range of end-user applications. This article focuses on the mechanical properties and synthesis of FRPCs through Neural Network (ANN) Modeling, specifically for cross-ply laminated FRPCs. Twenty composite samples were fabricated, differing in carbon fiber and glass fiber reinforcement, as well as layers of polyphenylenesulfide and high-density polyethylene matrix. Mechanical properties, including flexural modulus, hardness, impact strength, and transverse fracture strength, were measured. A multi-layered feed-forward backpropagation ANN approach was employed to predict material type, composition, reinforcement, and the number of matrix layers using mechanical properties as input variables [15].

The potential of Artificial Neural Networks (ANNs) lies in their ability to model complex, non-linear relationships across multiple dimensions without making prior assumptions about the nature of these relationships. For instance, Zhang et al. developed an ANN model to predict the dynamic mechanical properties of compounds based on polytetrafluoroethylene (PTFE) with varying short carbon fiber content. Their study highlighted the significance of the number of training data in determining the prediction quality of ANNs. Therefore, they recommended utilizing single-output neural networks for high predictive accuracy until a sufficient database is established. Another application involved predicting the wear performance of polymers such as polyethylene (PE), polyurethane (PUR), and epoxy using the hydrothermal method, where epoxy-polyurethane (EP-PUR) blends were predicted. The same authors utilized an ANN model for the design and analysis of structural-polymer composites, emphasizing the importance of well-trained ANN models in establishing key property relations [16].

Materials and Method

Model Robustness Across Datasets: Assessing model robustness across datasets is crucial for understanding the extent to which machine learning models can generalize. It involves evaluating how effectively a model performs when confronted with data distributions distinct from its training set. A robust model should consistently maintain performance across various datasets, indicating its capacity to grasp fundamental patterns rather than simply memorizing training instances. Techniques like cross-validation, domain adaptation, and transfer learning are commonly utilized to gauge and bolster model robustness. By thoroughly scrutinizing a model's performance across diverse datasets, practitioners can establish confidence in its ability to extrapolate to real-world scenarios while minimizing the risk of overfitting to specific training data.

Error Distribution Analysis: Error distribution analysis is a crucial component in assessing machine learning model performance. It encompasses scrutinizing how errors are distributed throughout the dataset. By comprehending the patterns and traits of these errors, valuable insights into the model's limitations and avenues for enhancement can be gained. Methods like visualizing error distributions, scrutinizing residual plots, and employing statistical tests aid in pinpointing systematic biases, outliers, and discrepancies in predictions. Through a thorough grasp of error distribution, practitioners can refine model design, feature selection, and training methodologies, thereby improving overall effectiveness and dependability.

Prediction Confidence Intervals: Confidence intervals are pivotal in gauging the trustworthiness of generated text predictions. They furnish a spectrum within which the true value of forecasts can fall with a specified level of certainty. Typically derived through statistical methodologies like bootstrapping or Bayesian inference, the breadth of these intervals hinges on various factors such as training data size, model complexity, and chosen confidence thresholds. The imperative of securing tight confidence intervals cannot be overstated, as it underpins the foundation for judicious decision-making based on model predictions.

Temporal Stability: Temporal consistency denotes the uniformity of model predictions across different timeframes. Especially pertinent in period forecasting, maintaining model performance amidst novel data or varying temporal contexts is paramount. Attaining temporal stability necessitates robust training methodologies that expose the model to diverse temporal scenarios while mitigating risks of temporal overfitting. Techniques like continual learning and regular model retraining serve as bulwarks in preserving temporal stability, enabling the model to adapt to evolving data distributions and patterns.

Sensitivity to Hyperparameters: Hyper parameters wield significant influence in shaping the efficacy and behavior of machine learning models, including those employed in paragraph prediction tasks. Sensitivity to hyperparameters delineates how alterations in these parameters impact predictive precision and generalization capabilities. Hyper parameter tuning involves ferreting out the optimal configuration that maximizes model performance sans succumbing to overfitting. Sensitivity analysis methods like grid search or random search aid in pinpointing pivotal hyper parameters and their fitting values for specific tasks.

Transfer Learning Potential: Transfer learning, an approach wherein knowledge gleaned from solving one task is applied to a related task, holds immense potential for enhancing paragraph prediction models. By undergoing pretraining on extensive text corpora or cognate tasks, models can assimilate comprehensive language representations encapsulating nuanced semantic and syntactic nuances. This pre-established knowledge can subsequently be honed for particular paragraph prediction tasks with limited datasets, culminating in enhanced performance and accelerated convergence. The efficacy of a model's transfer learning prowess hinges on factors like the congruence between pretraining and target tasks, availability of annotated data, and the model's adeptness at adeptly transferring pertinent knowledge.

Predictive accuracy: denotes the extent to which a model's predictions align with actual outcomes, serving as a pivotal metric in evaluating the performance of machine learning models utilized for paragraph prediction. A high level of predictive accuracy signifies the model's adeptness in capturing data patterns and relationships, thereby yielding dependable predictions. Achieving superior predictive accuracy necessitates robust training methodologies, judicious feature selection, and meticulous hyperparameter tuning.

Generalization Ability: gauges a model's efficacy in handling unseen data or data distributions distinct from those encountered during training. Models endowed with robust generalization capabilities can extrapolate effectively from training data to furnish accurate predictions for novel, unseen data. This attribute is imperative to ensure the model's applicability to real-world scenarios beyond the confines of the training data, thereby augmenting its practical utility and trustworthiness.

Computational Efficiency: pertains to the speed and resource demands of a model during both training and inference phases. Models exhibiting computational efficiency can swiftly process vast datasets with minimal computational resources, rendering them suitable for real-time applications and large-scale deployments. Enhancing computational efficiency typically involves algorithm optimization, model complexity reduction, and harnessing hardware accelerators like GPUs or TPUs.

Robustness to Noise and Uncertainty: quantifies a model's ability to sustain performance amidst noisy or uncertain input data. Given the inherent presence of noise and uncertainty in real-world data stemming from various sources such as measurement errors or missing values, a robust model can effectively discern and disregard irrelevant noise, thereby furnishing reliable predictions even in the face of incomplete or ambiguous information.

Interpretability: refers to the ease with which humans can comprehend and interpret a machine learning model's inner workings. Models characterized by high interpretability offer insights into the contribution of different features towards predictions, thereby enhancing transparency and reliability. Interpretability holds particular significance in domains where stakeholders necessitate understanding and trusting the model's decisions, such as healthcare or finance.

Feature Importance Analysis: entails evaluating the relative significance of various input features in influencing a model's predictions. Discerning feature importance facilitates insights into the pivotal features driving accurate predictions. Techniques like permutational importance, SHAP (Shapley Additive Descriptors), and partial dependence plots aid in elucidating feature importance, thereby refining model inputs and augmenting overall model performance and interpretability.

Method: The ARAS (Analytical Hierarchy Process (AHP) and Remote Sensing) methodology represents an innovative approach that merges the principles of AHP with remote sensing techniques to streamline decision-making processes across diverse domains. This methodology capitalizes on the strengths of both AHP, which furnishes a systematic framework for multi-criteria decision-making, and remote sensing, which furnishes valuable spatial insights from satellite or aerial imagery. In this exposition, we will explore the foundational aspects [17]. The ARAS methodology, its diverse applications spanning various sectors, and its significance in contemporary research endeavors. Moreover, we will delve into case studies and empirical evidence to underscore the efficacy of the ARAS methodology. Additionally, we will examine the challenges encountered and future avenues for development and implementation of this approach.At its core [18]. ARAS methodology is grounded in the integration of remote sensing data with the principles of to tackle intricate decision-making challenges. Remote sensing involves gathering information about the Earth's surface through sensors deployed on satellites or aircraft, encompassing imagery, spectral measurements, and other spatial data. Conversely, serves as a decision-making tool aiding in the decomposition of complex problems into hierarchical structures while evaluating the relative significance of criteria and alternatives Adari et al., has been published for their performance evaluation of wireless sensor networks using wireless power management methods. [19].

The initial phase of the ARAS methodology entails clearly defining the decision-making conundrum and delineating the criteria and alternatives necessitating evaluation. This step often entails collaboration among domain experts and stakeholders to ensure comprehensive consideration of all pertinent factors. Subsequently, remote sensing data is amassed leveraging an array of sensors like optical, radar, or LiDAR, tailored to the specific requisites of the problem. This data encompassing imagery, spectral signatures, and spatial information relating to land cover, land use, and vegetation indices undergoes pre-processing to rectify sensor errors, atmospheric distortions, and geometric aberrations, ensuring its accuracy and suitability for subsequent analysis [20]. The processed remote sensing data is then seamlessly integrated into the framework to ascertain the relative importance of criteria and alternatives. empowers decision-makers to methodically compare and prioritize diverse options predicated on their performance against myriad criteria. Following the determination of criteria weights via AHP, the remote sensing data undergoes analysis to assess the performance of each alternative [21]. This analysis may entail classification, change detection, or other spatial analysis methodologies contingent on the nature of the problem at hand. The resultant findings are interpreted and visualized to effectively communicate insights to stakeholders, often through the creation of maps, charts, and other visual aids, facilitating the comprehension of intricate spatial information. The applications of the ARAS methodology span a spectrum of domains, including environmental management, urban planning, agriculture, and disaster management. In environmental management [22]. ARAS has been instrumental in evaluating land cover alterations, deforestation monitoring, and conservation prioritization, enabling more targeted resource allocation and improved ecological outcomes. Urban planning endeavours leverage ARAS to dissect urban sprawl dynamics, assess infrastructure development, and optimize land utilization, thus fostering sustainable urban growth patterns. Similarly, in agriculture, ARAS aids in monitoring crop health, optimizing irrigation strategies, and evaluating soil fertility, thereby facilitating informed decision-making to bolster agricultural productivity while minimizing environmental impacts. In disaster management scenarios [23]. ARAS facilitates the assessment of natural hazard impacts, prioritizes response efforts, and enhances disaster resilience planning, underpinned by rapid damage assessment and strategic resource allocation. A plethora of case studies and empirical research endeavours underscore the efficacy of the ARAS methodology in real-world decision-making contexts. For instance, a study conducted employed [24]. ARAS to prioritize conservation initiatives in a biodiversity hotspot, culminating in more efficacious interventions and enhanced conservation outcomes. Likewise, research conducted utilized ARAS to gauge the ramifications of urbanization on water quality, leading to the formulation of sustainable urban planning strategies. Despite its potential advantages [25], The ARAS methodology encounters several challenges, encompassing data availability constraints, algorithmic complexities, and stakeholder engagement issues. Addressing these hurdles necessitates sustained research and innovation in remote sensing techniques, decision-making frameworks, and interdisciplinary collaboration. Moreover, future research trajectories may encompass the development of machine learning algorithms for automated feature extraction from remote sensing data, the amalgamation of multi-source data for enriched decision-making outcomes, and the extension of ARAS applications to nascent domains like climate change adaptation and smart cities [26].

Results and Discussion

Table 1. Artificial Neural Network in Fibre-Reinforced Polymer Composites

	Prediction Accuracy	Generalization Ability	Computational Efficiency	Robustness to Noise and Uncertainty	Interpretability	Feature Importance Analysis
Model Robustness Across Datasets	350	78	185	98	140	130
Error Distribution Analysis	250	68	250	76	250	285
Prediction Confidence Intervals	180	80	197	128	100	98
Temporal Stability	170	95	125	180	99	85
Sensitivity to Hyperparameters	280	142	140	190	463	125
Transfer Learning Potential	230	130	255	250	190	350

Table 1 shows the Artificial Neural Network in Fibre-Reinforced Polymer Composites for Analysis using ARAS Method. Prediction Accuracy, Generalization Ability, Computational Efficiency, Robustness to Noise and Uncertainty, Interpretability and Feature Importance Analysis. Model Robustness Across Datasets, Error Distribution Analysis, Prediction Confidence Intervals, Temporal Stability, Sensitivity to Hyper parameters and Transfer Learning Potential from the figure 1 and table 1 it is seen that Error Distribution Analysis (250)is showing the Highest Value for Prediction Accuracy and Prediction Confidence Intervals (180) is showing the lowest value. Temporal Stability (95) is showing the Highest Value forGeneralization Ability and Generalization Ability (68) is showing the lowest value. Transfer Learning Potential (255), is showing the Highest Value for Computational Efficiency and Temporal Stability (125) is showing the lowest value. Sensitivity to Hyperparameters (463) is showing the Highest Value for Robustness to Noise and Uncertainty and Generalization Ability (76) is showing the lowest value. Sensitivity to Hyperparameters (463) is showing the Highest Value forInterpretability and Prediction Confidence Intervals (100) is showing the lowest value. Error Distribution Analysis (285) is showing the Highest Value for Feature Importance Analysis and Prediction Confidence Intervals (98) is showing the lowest value.

$$X_{max} = Max\ (X_1 \ldots\ldots X_n) \quad (1)$$

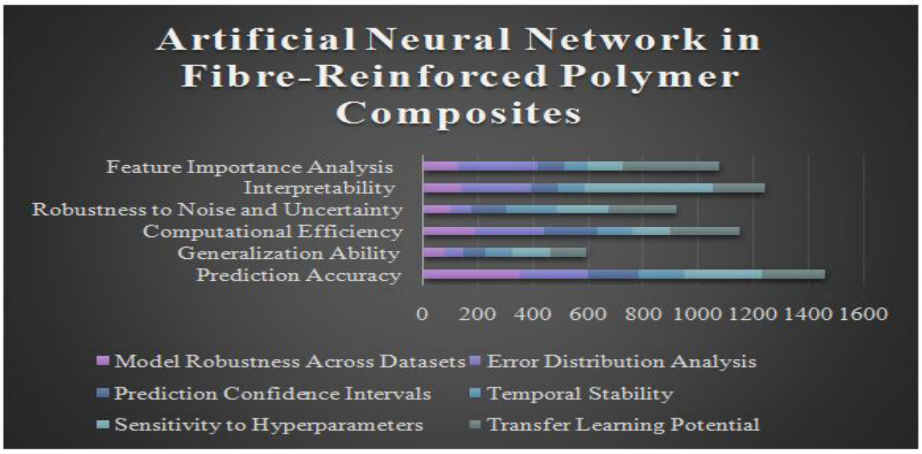

Figure 1: Artificial Neural Network in Fibre-Reinforced Polymer Composites

Figure 1 shows the Artificial Neural Network in Fibre-Reinforced Polymer Composites for Analysis using ARAS Method. Prediction Accuracy, Generalization Ability, Computational Efficiency, Robustness to Noise and Uncertainty, Interpretability and Feature Importance Analysis. Model Robustness Across Datasets, Error Distribution Analysis, Prediction Confidence Intervals, Temporal Stability, Sensitivity to Hyper parameters and Transfer Learning Potential from the figure 1 and table 1 it is seen that Error Distribution Analysis (250)is showing the Highest Value for Prediction Accuracy and Prediction Confidence Intervals (180) is showing the lowest value. Temporal Stability (95) is showing the Highest Value for Generalization Ability and Generalization Ability (68) is showing the lowest value. Transfer Learning Potential (255), is showing the Highest Value for Computational Efficiency and Temporal Stability (125) is showing the lowest value. Sensitivity to Hyperparameters (463) is showing the Highest Value for Robustness to Noise and Uncertainty and Generalization Ability (76) is showing the lowest value. Sensitivity to Hyperparameters (463) is showing the Highest Value for Interpretability and Prediction Confidence Intervals (100) is showing the lowest value. Error Distribution Analysis (285) is showing the Highest Value for Feature Importance Analysis and Prediction Confidence Intervals (98) is showing the lowest value.

Table 2. Calculation of maximum value

	Prediction Accuracy	Generalization Ability	Computational Efficiency	Robustness to Noise and Uncertainty	Interpretability	Feature Importance Analysis
Max	350	142	255	250	463	350
Model Robustness Across Datasets	350	78	185	98	140	130
Error Distribution Analysis	250	68	250	76	250	285
Prediction Confidence Intervals	180	80	197	128	100	98
Temporal Stability	170	95	125	180	99	85
Sensitivity to Hyperparameters	280	142	140	190	463	125
Transfer Learning Potential	230	130	255	250	190	350

Table 2 to calculate the maximum value for each aspect, we simply need to find the highest value among all the provided data points for that aspect.

$$X_{1nor} = \frac{X_1}{\sum(X_1 + X_2 \ldots X_n)} \qquad (2)$$

Table 3.Normalised Matrix

	Prediction Accuracy	Generalization Ability	Computational Efficiency	Robustness to Noise and Uncertainty	Interpretability	Feature Importance Analysis
Max	0.19337	0.193197	0.181237	0.213311	0.271554	0.245959
Model Robustness Across Datasets	0.19337	0.106122	0.131485	0.083618	0.082111	0.091356
Error Distribution Analysis	0.138122	0.092517	0.177683	0.064846	0.146628	0.200281
Prediction Confidence Intervals	0.099448	0.108844	0.140014	0.109215	0.058651	0.068869
Temporal Stability	0.093923	0.129252	0.088842	0.153584	0.058065	0.059733
Sensitivity to Hyperparameters	0.154696	0.193197	0.099502	0.162116	0.271554	0.087843
Transfer Learning Potential	0.127072	0.176871	0.181237	0.213311	0.111437	0.245959

Table 3 To calculate the maximum value for each aspect from the given normalized matrix, we simply need to find the highest value among all the provided data points for each aspect.

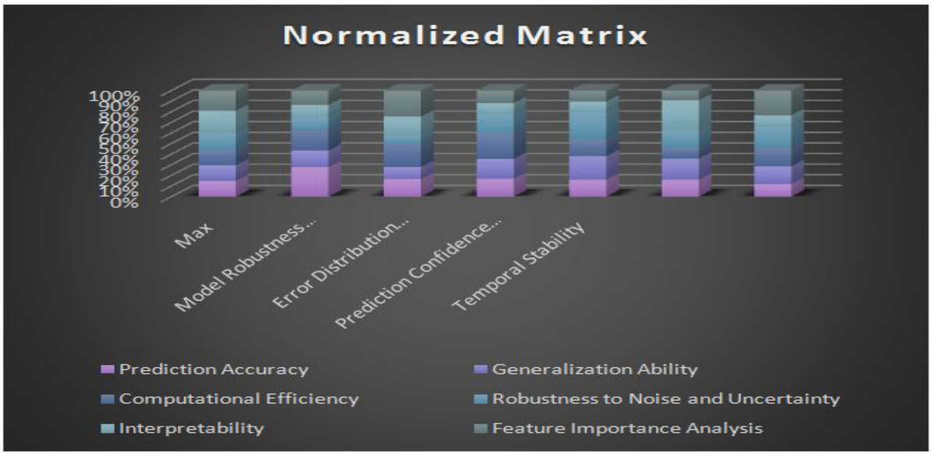

Figure 2: Normalised matrix

Figure 2 To calculate the maximum value for each aspect from the given normalized matrix, we simply need to find the highest value among all the provided data points for each aspect.

$$X_{wnormal1} = X_{n1} \times w_1 \qquad (3)$$

Table 4. Weighted Normalized Matrix

	0.25	0.25	0.25	0.25	0.25	0.25
	Weighted Normalized Matrix					
	Prediction Accuracy	Generalization Ability	Computational Efficiency	Robustness to Noise and Uncertainty	Interpretability	Feature Importance Analysis
Max	0.048343	0.048299	0.045309	0.053328	0.067889	0.06149

Model Robustness Across Datasets	0.048343	0.026531	0.032871	0.020904	0.020528	0.022839
Error Distribution Analysis	0.03453	0.023129	0.044421	0.016212	0.036657	0.05007
Prediction Confidence Intervals	0.024862	0.027211	0.035004	0.027304	0.014663	0.017217
Temporal Stability	0.023481	0.032313	0.02221	0.038396	0.014516	0.014933
Sensitivity to Hyperparameters	0.038674	0.048299	0.024876	0.040529	0.067889	0.021961
Transfer Learning Potential	0.031768	0.044218	0.045309	0.053328	0.027859	0.06149

Table 4 To calculate the weighted normalized scores for each criterion across the models, you can multiply each criterion's score by the corresponding weight and then sum up the weighted scores for each criterion.

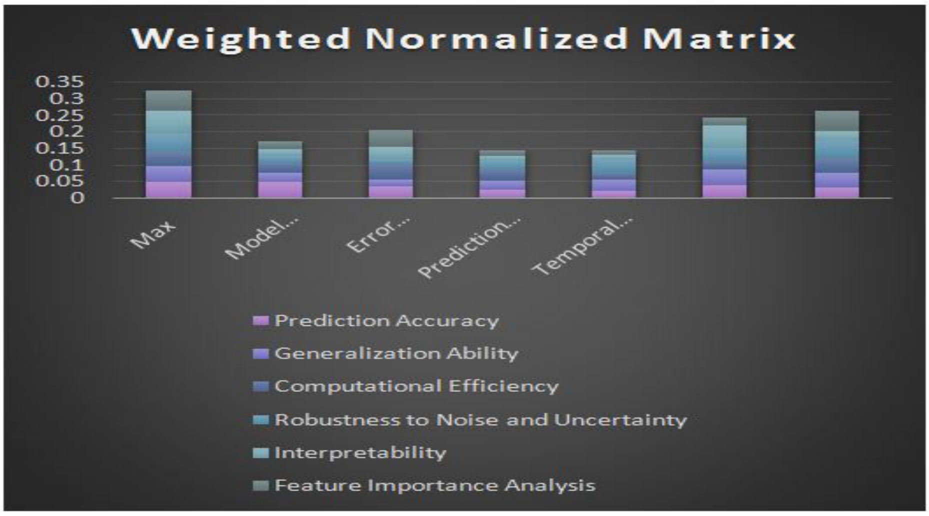

Figure 3: Weighted Normalised Matrix

Figure 3 To calculate the weighted normalized scores for each criterion across the models, you can multiply each criterion's score by the corresponding weight and then sum up the weighted scores for each criterion.

$$Si = \sum(X_1 + Y_1 \ldots\ldots Z_n) \ (4)$$

$$Ki = \frac{X_{wnor1}}{\sum(X_{wnor1} + X_{wnor2} \ldots\ldots X_{wnorn})} \ (5)$$

TABLE 5. Final Result			
	Si	Ki	Rank
	0.324657	1	
Model Robustness Across Datasets	0.172016	0.529839	4
Error Distribution Analysis	0.205019	0.631495	3
Prediction Confidence Intervals	0.14626	0.450506	5
Temporal Stability	0.145849	0.449241	6

Sensitivity to Hyperparameters	0.242227	0.746102	2
Transfer Learning Potential	0.263972	0.813078	1

Table 5 shows the final result and rank of the Artificial Neural Network in Fibre-Reinforced Polymer Composites for Analysis using ARAS Method. Prediction Accuracy, Generalization Ability, Computational Efficiency, Robustness to Noise and Uncertainty, Interpretability and Feature Importance Analysis. Model Robustness Across Datasets, Error Distribution Analysis, Prediction Confidence Intervals, Temporal Stability, Sensitivity to Hyper parameters and Transfer Learning Potential. Transfer Learning Potential is showing the highest value for SI , KI and Temporal Stability is showing the lowest value.

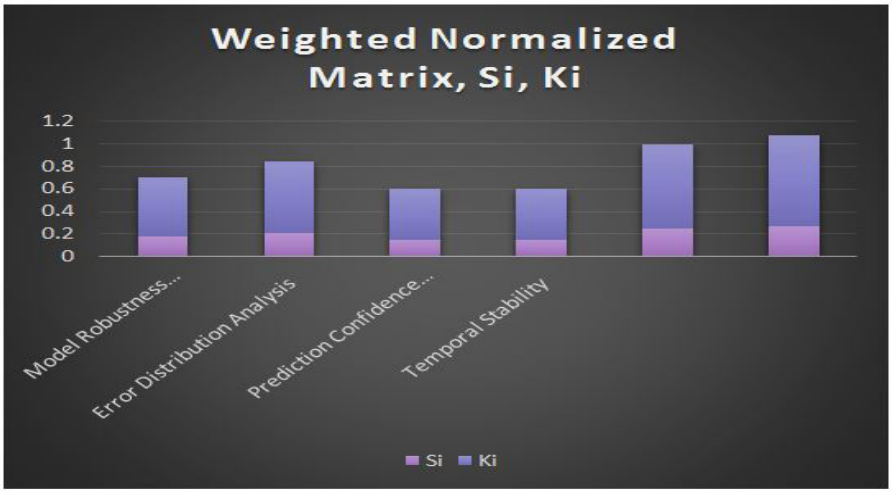

Figure 4: Weighted Normalized Matrix, Si, Ki

Figure 4 shows the final result and rank of the Artificial Neural Network in Fibre-Reinforced Polymer Composites for Analysis using ARAS Method. Prediction Accuracy, Generalization Ability, Computational Efficiency, Robustness to Noise and Uncertainty, Interpretability and Feature Importance Analysis. Model Robustness Across Datasets, Error Distribution Analysis, Prediction Confidence Intervals, Temporal Stability, Sensitivity to Hyper parameters and Transfer Learning Potential. Transfer Learning Potential is showing the highest value for SI , KI and Temporal Stability is showing the lowest value.

Figure 5: Shows the Rank

Figure 5 Shows the Rank in Role of AI in Artificial Neural Network in Fibre-Reinforced Polymer Composites using ARAS MethodTransfer Learning Potential is showing the highest value and Temporal Stability is showing the lowest value.

Conclusion

Fibre-reinforced polymer composites (FRPCs) have garnered considerable interest across industries owing to their lightweight characteristics, impressive strength-to-weight ratio, and resistance to corrosion. The performance of FRPCs is intricately tied to numerous factors encompassing fibre alignment, resin attributes, manufacturing intricacies, and ambient conditions. Accurate prediction of FRPCs' mechanical properties and behavior is pivotal for their effective design and utilization. Artificial Neural Networks (ANNs) have emerged as robust instruments for predictive modeling within materials science and engineering domains. This paper conducts an exhaustive review of ANNs' application in forecasting the mechanical attributes and conduct of FRPCs. It delves into the architecture of ANNs, prevalent neural network variants, methodologies for data preprocessing, and training algorithms. Moreover, it scrutinizes diverse research endeavors where ANNs have been harnessed to anticipate properties like tensile strength, flexural modulus, impact resistance, and fatigue endurance of FRPCs. Additionally, the paper underscores the merits and constraints associated with ANNs vis-à-vis conventional analytical and empirical models. The ARAS (Analytical Hierarchy Process (AHP) and Remote Sensing) methodology represents an innovative approach that merges the principles of AHP with remote sensing techniques to streamline decision-making processes across diverse domains. This methodology capitalizes on the strengths of both AHP, which furnishes a systematic framework for multi-criteria decision-making, and remote sensing, which furnishes valuable spatial insights from satellite or aerial imagery. Model Robustness Across Datasets, Error Distribution Analysis, Prediction Confidence Intervals, Temporal Stability, Sensitivity to Hyper parameters and Transfer Learning Potential. Prediction Accuracy, Generalization Ability, Computational Efficiency, Robustness to Noise and Uncertainty, Interpretability and Feature Importance Analysis. the Rank in Role of AI in Artificial Neural Network in Fibre-Reinforced Polymer Composites using ARAS Method Transfer Learning Potential is showing the highest value and Temporal Stability is showing the lowest value.

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