



# A Comprehensive Review of Hybrid and Ensemble Methods in Machine Learning Modeling

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**Abstract:** Conventional machine learning (ML) algorithms are rapidly advancing with the introduction of novel learning techniques. These models are continuously improving through hybridization and ensemble approaches, enhancing their computational efficiency, functionality, robustness, and accuracy. In recent years, numerous hybrid and ensemble ML models have been proposed. However, a comprehensive survey of these models is still lacking. This paper aims to address this gap by presenting a state-of-the-art review of emerging ML models, highlighting their performance, applications, and categorization through a novel taxonomy.

**Keywords:** machine learning; deep learning; ensemble models

## Nomenclatures

| Definition                                        | Abbreviation | Definition                                                                         | Abbreviation |
|---------------------------------------------------|--------------|------------------------------------------------------------------------------------|--------------|
| Artificial neural network                         | ANN          | Bagging-based naïve bayes trees                                                    | BAGNBT       |
| Extreme learning machine                          | ELM          | Ensemble empirical mode decomposition                                              | EEMD         |
| Machine learning                                  | ML           | Grasshopper optimization algorithm                                                 | GOA          |
| Support vector machine                            | SVM          | Hybrid of linear regression-deep neural network                                    | HybPAS       |
| Wavelet neural networks                           | WNN          | Trauma Severity model                                                              | TSM          |
| Deep learning                                     | DL           | Gradient boosting decision tree                                                    | GBDT         |
| Autoregressive integrated moving average          | ARIMA        | Evidential belief function and tree based models                                   | EBFTM        |
| Ensemble empirical with adaptive noise technology | EE ANT       | Decision tree overfitting and neural network                                       | DTFNN        |
| Data assimilation Kalman filter-based             | DA-KF        | Improved complete ensemble empirical mode decomposition method with adaptive noise | ICEEMDMAN    |
| Online sequential extreme learning machine        | OSELM        | Random forest                                                                      | RF           |

## 1. INTRODUCTION

Machine learning (ML) techniques have been reported to outperform most traditional physical and statistical approaches in predictive modeling, offering superior accuracy, robustness, uncertainty handling, data efficiency, simplicity, and computational efficiency. Consequently, ML methods have gained significant popularity in recent years and are now widely applied across diverse domains, including energy, hydrology, hazard prediction, finance, economics, and computational mechanics [1–9].



A wide variety of ML methods exist, and several classification schemes have been proposed by researchers [10–13]. One widely adopted approach categorizes ML techniques into three groups: single methods, hybrid methods, and ensemble methods [14–16]. Among the most commonly used single ML approaches are artificial neural networks (ANNs) [17–19], decision trees (DTs) [18, 20–23], support vector machines (SVMs) [24–27], Bayesian models [28–30], neuro-fuzzy systems [11, 12, 31, 32], classification and regression techniques [33], and wavelet neural networks (WNNs) [12, 34]. Although neuro-fuzzy systems and WNNs integrate two intelligent algorithms, they are generally categorized as single-method approaches due to their structural formulation.

ML techniques continue to evolve, driving the development of increasingly powerful algorithms aimed at achieving higher predictive performance [35–49]. In particular, hybrid **and** ensemble methods have gained attention for their ability to consistently outperform traditional single-method approaches [50–60].

Ensemble and hybrid machine learning (ML) approaches represent two of the most promising directions for achieving higher accuracy, reliability, and robustness in predictive modeling [61–63]. Hybrid ML models are developed by integrating multiple ML algorithms and/or combining them with other soft computing techniques, optimization strategies, or statistical approaches to enhance performance across various dimensions. In contrast, ensemble methods rely on grouping strategies—such as bagging, boosting, and stacking—to leverage the predictive capabilities of multiple classifiers simultaneously.

Recent studies suggest that the future success of ML will largely depend on advancements in novel ensemble and hybrid techniques [32, 64–66]. The existing literature includes several innovative ML methods and comparative analyses aimed at identifying models with superior performance [67–69]. However, a significant research gap remains in systematically identifying novel hybrid and ensemble ML approaches and mapping their application domains. To address this gap, the present study introduces these emerging techniques and highlights their practical applications across diverse fields.

## II. REVIEWING ENSEMBLE AND HYBRID ML METHODS

The adoption of machine learning (ML) techniques—including single models, ensemble approaches, and hybrid frameworks—has grown exponentially in recent years. *Figure 1* illustrates the rapid and continuous rise in the use of ML methods from 2009 to the present. These techniques have found widespread applications across a broad spectrum of disciplines, including engineering, mathematics, physics, astronomy, earth and planetary sciences, medicine, materials science, biochemistry, genetics and molecular biology, environmental science, social sciences, energy, chemistry, decision sciences, as well as agricultural and biological sciences.

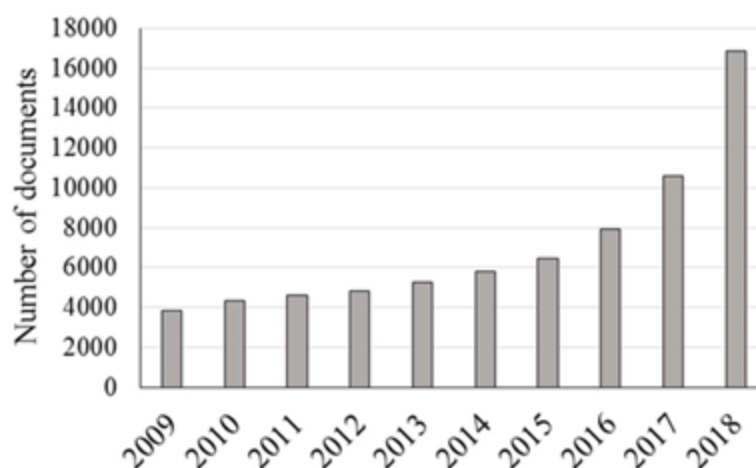


Figure 1 The growing trend of ML methods the past decade (source: web of science).

In the following, Figure.2 shows the popularity of ensemble and hybrid ML models in advancing the novel method with higher performance.

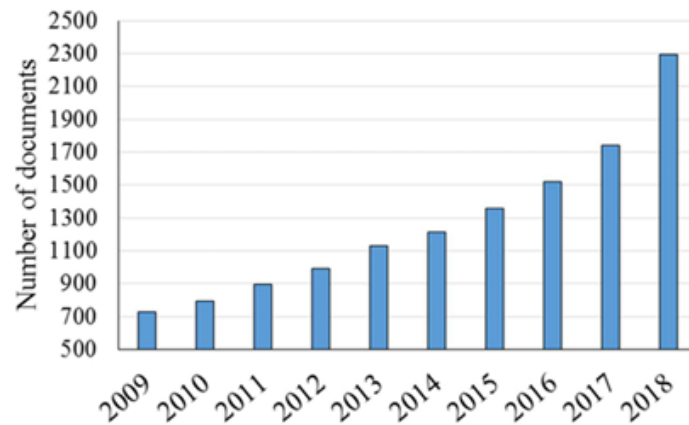


Figure 2 The growing trend of hybrid and ensemble ML methods (source: web of science).

### 2.1. Hybrid methods

Hybrid machine learning (ML) methods integrate two or more ML algorithms and/or soft computing techniques to achieve enhanced performance and optimal results. By leveraging the complementary strengths of multiple approaches, hybrid models are capable of delivering superior accuracy, robustness, and adaptability compared to single-method techniques. In many cases, hybrid frameworks consist of two core components: one dedicated to prediction and the other focused on optimizing the predictive model, thereby improving overall reliability and precision.

Due to their flexibility and ability to exploit the strengths of different algorithms, hybrid methods have gained significant popularity in recent years. Conceptually, they can be compared to a team of experts—each specializing in different areas—working together to achieve a common objective.

Table 1 summarizes the top six studies that utilize hybrid methods. The table presents four key aspects for each study: the reference, the primary contribution, the developed hybrid model, and the application domain. This provides a concise overview, enabling readers to quickly identify the main highlights and relevance of each work.

Table 1 Studies developed by hybrid methods.

| References | Contributions                                                                                                  | Methods                   | Application domains                                        |
|------------|----------------------------------------------------------------------------------------------------------------|---------------------------|------------------------------------------------------------|
| [70]       | To develop an adaptive hybrid methodology for the estimation of urban traffic flow                             | ARIMA<br>WNN -            | - Urban traffic flow<br>- Advanced hybrid machine learning |
| [71]       | To develop an innovative hybrid method for the estimation and optimization of wind energy                      | EE-ANT<br>WNN -           | - Wind power<br>- Hybrid machine learning                  |
| [72]       | To develop a novel hybrid multi stage method to be applied in credit scoring                                   | Hybrid multi-stage method | - Classification<br>- Multi-stage hybrid model             |
| [73]       | To develop a novel hybrid bagging based method for the assessment of the Landslide susceptibility              | Hybrid BAGNBT             | - Landslide susceptibility<br>- Hybrid machine learning    |
| [74]       | To develop a hybrid method for the estimation of electricity load                                              | EEMD<br>ELM-<br>GOA       | - Electrical load<br>- Hybrid machine learning             |
| [75]       | To develop a hybrid linear regression-based deep learning method for the estimation of poly (A) signals in DNA | HybPAS                    | - Hybrid machine learning<br>- Signal processing           |

Hou et al. [70] conducted a study aimed at accurately estimating urban traffic flow. They proposed an advanced hybrid model integrating a wavelet neural network (WNN) with an autoregressive integrated moving average (ARIMA)



model, enhanced through a fuzzy-based approach. The hybrid method was compared against the individual single models using mean absolute percentage error (MAPE) and root mean square error (RMSE) metrics. The results demonstrated a 60–70% improvement in estimation accuracy compared to single-method models.

Similarly, Du et al. [71] developed a novel hybrid model for wind power estimation and optimization. Their approach combined an ensemble empirical mode decomposition (EEMD) integrated with adaptive noise technology to eliminate noise and extract significant data features, followed by an optimized wavelet neural network for enhanced prediction accuracy. The proposed hybrid approach was evaluated using MAPE, and the results confirmed substantial improvements in both estimation accuracy and the sustainability of prediction and optimization processes.

Zhang et al. [72] introduced a feature-and-classifier-based hybrid model designed to improve credit scoring accuracy. The proposed framework simultaneously selected the optimal classifier and feature subset using a classifier ensemble coupled with an enhanced multi-population niche genetic algorithm (EMNGA). Evaluations conducted using accuracy and area under the curve (AUC) demonstrated that the hybrid method significantly outperformed single-method approaches in both estimation and optimization tasks.

Pham and Prakash [73] developed a bagging-based Naïve Bayes Trees (BAGNBT) model for landslide susceptibility assessment. The proposed hybrid method was compared with several single models, including Rotation Forest-based Naïve Bayes Trees, Naïve Bayes Trees, and support vector machines (SVM), using AUC and other statistical indices. Results revealed that the BAGNBT model achieved superior accuracy and could be considered a reliable alternative for landslide susceptibility prediction compared to single-method approaches.

Wu et al. [74] proposed an advanced hybrid forecasting framework for improving electricity load prediction. Their approach integrated an Extreme Learning Machine (ELM), ensemble empirical mode decomposition (EEMD), and the grasshopper optimization algorithm (GOA). Evaluations based on RMSE, mean absolute error (MAE), and MAPE demonstrated that the proposed model significantly outperformed individual models, achieving higher accuracy and predictive stability.

In another study, Albalawi et al. [75] developed HybPAS, a hybrid model integrating linear regression and deep neural network (DNN) architectures, for predicting  $\text{ply}(a)$  signals in DNA using sequence-based features and signal-processing-based statistical inputs. Experimental results indicated that HybPAS improved predictive accuracy and performance by 30.29% compared to single-method baselines.

From this brief review, it is evident that hybrid ML methods are rapidly gaining popularity due to their high potential, adaptability, and capability in improving estimation accuracy and optimization performance across various domains. Table 2 provides a concise yet comprehensive comparison of single and hybrid methods in terms of accuracy, reliability, and sustainability.

Table 2 Studies developed by hybrid methods.

| Method                                  | Application | Accuracy | Reliability | Sustainability | Reference |
|-----------------------------------------|-------------|----------|-------------|----------------|-----------|
| Hybrid WNN-ARIMA                        | Estimation  | +++      | +++         | +++            | [70]      |
| WNN                                     | Estimation  | ++       | ++          | ++             | [70]      |
| ARIMA                                   | Estimation  | ++       | +           | +              | [70]      |
| Hybrid EE-ANT-WNN                       | Estimation  | +++      | +++         | +++            | [71]      |
| Hybrid the optimized multi stage method | Estimation  | +++      | +++         | +++            | [72]      |
| BAGNBT                                  | Estimation  | +++      | +++         | +++            | [73]      |
| SVM                                     | Estimation  | ++       | +           | +              | [73]      |
| NBT                                     | Estimation  | +        | +           | +              | [73]      |
| RFNBT                                   | Estimation  | ++       | ++          | ++             | [73]      |
| EEMD-ELM-GOA                            | Estimation  | +++      | +++         | +++            | [74]      |

## 2.2. Ensemble methods

Ensemble machine learning (ML) methods employ a collection of classifiers—such as multiple decision trees—instead of relying on a single model. By aggregating the predictions of several learners, ensemble techniques significantly



enhance overall accuracy, robustness, and generalization performance. These approaches are typically categorized under supervised learning algorithms and are designed to improve predictive capability by combining the strengths of multiple base learners.

Ensemble methods leverage diverse training algorithms to reduce variance, minimize bias, and enhance stability, ultimately achieving higher testing accuracy. By enabling flexible integration of various classifiers, ensemble frameworks offer improved adaptability and reliability compared to single-method models.

Table 3 summarizes the top six studies that applied different ensemble techniques across various tasks. The table highlights each study's reference, key contribution, proposed ensemble method, and application domain, providing a concise comparative overview of their objectives and outcomes.

Table 3 Studies developed by Ensemble methods.

| References | Contributions                                                                                                            | Methods                   | Application domains                                      |
|------------|--------------------------------------------------------------------------------------------------------------------------|---------------------------|----------------------------------------------------------|
| [76]       | To develop an ensemble machine learning methodology for the estimation of risk                                           | Ensemble TSM              | - Risk prediction<br>- Ensemble machine learning         |
| [77]       | To develop an ensemble model to estimate the churn in the relation of customers and search Ads.                          | Ensemble GBDT             | - Customer churn<br>- Ensemble machine learning          |
| [78]       | To employ rotation forest with DT as an ensemble methodology based on EBF and tree-based models for developing GPM       | Ensemble EBFTM            | - Hydrogeology<br>- Ensemble machine learning            |
| [79]       | To develop a novel ensemble machine learning method integrated by ELM for the estimation of significant wave height      | Ensemble ICEEMDA N ELM    | - Wave height forecasting<br>- Ensemble machine learning |
| [80]       | To develop a novel Ensemble data assimilation Kalman filter-based for the estimation of parameters of the system's state | Ensemble DA KF            | - System's state<br>- Ensemble learning                  |
| [81]       | To develop an ensemble estimation model for forecasting the thyroid                                                      | Ensemble Bagging Boosting | - Thyroid forecasting<br>- Ensemble machine learning     |

Gorczyca et al. [76] developed a Trauma Severity Prediction Model based on an ensemble machine learning approach for accurate risk estimation. The proposed model was compared with established benchmarks, including the Harborview Assessment for Risk of Mortality (HARM), Bayesian Logistic Injury Severity Score (BLISS), and the Trauma Mortality Prediction Model (TMPM), using accuracy and F-score metrics. The results demonstrated that the ensemble model achieved superior predictive performance, indicating that trauma-related features are essential predictors for this task.

Wang et al. [77] proposed an ensemble gradient boosting decision tree (GBDT) model to estimate customer churn and its association with search advertisements, utilizing both dynamic and static features. The model was evaluated using the Bing Ads platform dataset, and results demonstrated highly accurate and sustainable performance, highlighting its effectiveness for real-world customer retention analytics.

Naghibi et al. [78] introduced an ensemble methodology based on evidential belief function and tree-based models (EBFTM), integrating rotation forests with decision trees to generate groundwater potential maps. The performance of the proposed ensemble method was compared against boosted regression trees (BRT), random forests (RF), and classification and regression trees (CART) using receiver operating characteristic (ROC) curves and area under the curve (AUC) metrics. Results revealed that the EBFTM ensemble achieved the highest prediction accuracy, outperforming RF, BRT, and CART models.

Ali and Prasad [79] developed a novel ensemble empirical mode decomposition (EEMD) framework combined with an



extreme learning machine (ELM) to accurately estimate significant wave heights. The proposed ICEEMDAN-ELM model was evaluated alongside ICEEMDAN-OSELM (EEMD integrated with an online sequential ELM) and ICEEMDAN-RF (EEMD integrated with a random forest). Experimental results demonstrated that ICEEMDAN-ELM achieved the highest accuracy and stability, outperforming both ICEEMDAN-OSELM and ICEEMDAN-RF in predictive performance.

Yamanaka et al. [80] proposed a novel ensemble framework based on data assimilation with Kalman filtering for microstructure prediction using three-dimensional multi-phase-field parameters. The method demonstrated significantly improved accuracy and produced the lowest prediction errors, confirming its capability for direct application in parameter estimation tasks.

Yadav and Pal [81] developed a Bagging-Boosting ensemble method for predicting women's thyroid disorders. The proposed approach was compared against the Decision Tree with Feature Neural Network (DTFNN) using root mean square error (RMSE) and mean absolute error (MAE) as evaluation metrics. Results revealed that the ensemble bagging-boosting model achieved approximately 65% higher accuracy than the DTFNN approach, highlighting its robustness and reliability.

From these studies, it is evident that ensemble machine learning methods have demonstrated superior performance, accuracy, and sustainability across diverse application domains. Their increasing adoption reflects their growing importance and research interest. Accordingly, Table 4 presents a concise yet comprehensive comparison of prominent ensemble-based methods, focusing on their accuracy, reliability, and practical applicability.

Table 4 the comparison results of Ensemble machine learning based methods.

| Method                    | Application | Accuracy | Reliability | Sustainability | Reference |
|---------------------------|-------------|----------|-------------|----------------|-----------|
| Ensemble TSM              | Estimation  | +++      | +++         | +++            | [76]      |
| Ensemble GBDT             | Estimation  | +++      | +++         | +++            | [77]      |
| Ensemble EBFTM            | Estimation  | +++      | +++         | +++            | [78]      |
| RF                        | Estimation  | +++      | ++          | ++             | [78]      |
| BRT                       | Estimation  | ++       | ++          | ++             | [78]      |
| ICEEMDAN-ELM              | Estimation  | +++      | +++         | +++            | [79]      |
| ICEEMDAN-OSELM            | Estimation  | ++       | +           | +              | [79]      |
| ICEEMDAN-RF               | Estimation  | ++       | ++          | ++             | [79]      |
| Ensemble KF-DA            | Estimation  | ++       | ++          | ++             | [80]      |
| Ensemble bagging-boosting | Estimation  | +++      | +++         | +++            | [81]      |
| DTFNN                     | Estimation  | ++       | +           | +              | [81]      |

### III. CONCLUSION

Ensemble and hybrid models represent the next generation of machine learning (ML) techniques, offering higher predictive accuracy, robustness, and efficiency compared to most conventional ML approaches. This paper provides a state-of-the-art review of hybrid and ensemble methodologies, highlighting their most prominent algorithms, comparative performance, and application domains.

Currently, ensembles are predominantly developed using decision-tree-based techniques; however, future advancements are expected to extend ensemble learning to a broader range of ML algorithms. Among existing approaches, bagging and boosting have emerged as the most widely adopted strategies for constructing ensemble models.

Hybrid models, on the other hand, are designed by integrating multiple ML algorithms, often combined with optimization techniques and soft computing methods, to enhance model performance and reliability. The primary application areas of ensemble and hybrid models include healthcare, energy systems, climate change prediction, urban informatics, and hydrology, among others.





Given their growing capabilities, future research directions are expected to focus on developing novel hybrid and ensemble architectures capable of delivering even greater accuracy, adaptability, and scalability across a diverse range of domains [82–91].

## REFERENCES

- [1]. Choubin, B., et al., Snow avalanche hazard prediction using machine learning methods. *Journal of Hydrology*, 2019. 577.
- [2]. Dehghani, M., et al., Prediction of hydropower generation using Grey wolf optimization adaptive neuro-fuzzy inference system. *Energies*, 2019. 12(2).
- [3]. Mosavi, A., Y. Bathla, and A. Varkonyi-Koczy, Predicting the future using web knowledge: State of the art survey, D. Luca, L. Sirghi, and C. Costin, Editors. 2018, Springer Verlag. p. 341-349.
- [4]. Mosavi, A. and T. Rabczuk, Learning and intelligent optimization for material design innovation, D.E. Kvasov, et al., Editors. 2017, Springer Verlag. p. 358-363.
- [5]. Mosavi, A., T. Rabczuk, and A.R. Varkonyi-Koczy, Reviewing the novel machine learning tools for materials design, D. Luca, L. Sirghi, and C. Costin, Editors. 2018, Springer Verlag. p. 50-58.
- [6]. Qasem, S.N., et al., Estimating daily dew point temperature using machine learning algorithms. *Water (Switzerland)*, 2019. 11(3).
- [7]. Taherei Ghazvinei, P., et al., Sugarcane growth prediction based on meteorological parameters using extreme learning machine and artificial neural network. *Engineering Applications of Computational Fluid Mechanics*, 2018. 12(1): p. 738-749.
- [8]. Torabi, M., et al., A Hybrid clustering and classification technique for forecasting short-term energy consumption. *Environmental Progress and Sustainable Energy*, 2019. 38(1): p. 66-76.
- [9]. Torabi, M., et al., A Hybrid Machine Learning Approach for Daily Prediction of Solar Radiation, in *Lecture Notes in Networks and Systems*. 2019, Springer. p. 266-274.
- [10]. Dineva, A., et al., Review of soft computing models in design and control of rotating electrical machines. *Energies*, 2019. 12(6).
- [11]. Mosavi, A., P. Ozturk, and K.W. Chau, Flood prediction using machine learning models: Literature review. *Water (Switzerland)*, 2018. 10(11).
- [12]. Mosavi, A., et al., State of the art of machine learning models in energy systems, a systematic review. *Energies*, 2019. 12(7).
- [13]. Mosavi, A. and A.R. Varkonyi-Koczy, Integration of machine learning and optimization for robot learning, R. Jablonski and R. Szweczyk, Editors. 2017, Springer Verlag. p. 349-355.
- [14]. Cheng, L. and T. Yu, A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems. *International Journal of Energy Research*, 2019. 43(6): p. 1928-1973.
- [15]. Cheng, L., et al., Machine Learning for Energy and Electric Power Systems: State of the Art and Prospects. *Dianli Xitong Zidonghua/Automation of Electric Power Systems*, 2019. 43(1): p. 15-31.
- [16]. Chou, J.S. and D.S. Tran, Forecasting energy consumption time series using machine learning techniques based on usage patterns of residential householders. *Energy*, 2018: p. 709-726.
- [17]. Chatterjee, B., et al., RF-PUF: Enhancing IoT Security Through Authentication of Wireless Nodes Using In-Situ Machine Learning. *IEEE Internet of Things Journal*, 2019. 6(1): p. 388-398.
- [18]. Panesar, S.S., et al., Machine Learning Versus Logistic Regression Methods for 2-Year Mortality Prognostication in a Small, Heterogeneous Glioma Database. *World Neurosurgery*: X, 2019. 2.
- [19]. Thomas, P.B.M., et al., Feasibility of simple machine learning approaches to support detection of non-glaucomatous visual fields in future automated glaucoma clinics. *Eye (Basingstoke)*, 2019. 33(7): p. 1133-1139.
- [20]. Alhajri, M.I., N.T. Ali, and R.M. Shubair, Classification of Indoor Environments for IoT Applications: A Machine Learning Approach. *IEEE Antennas and Wireless Propagation Letters*, 2018. 17(12): p. 2164-2168.
- [21]. Jamil, A. and B. Bayram, The delineation of tea gardens from high resolution digital orthoimages using mean-shift and supervised machine learning methods. *Geocarto International*, 2019.
- [22]. Maxwell, A.E., T.A. Warner, and F. Fang, Implementation of machine-learning classification in remote sensing: An applied review. *International Journal of Remote Sensing*, 2018. 39(9): p. 2784-2817.
- [23]. Sehgal, V., et al., Machine learning creates a simple endoscopic classification system that improves dysplasia detection in barrett's oesophagus amongst non-expert endoscopists. *Gastroenterology Research and Practice*, 2018. 2018.
- [24]. Azeem, M.I., et al., Machine learning techniques for code smell detection: A systematic literature review and meta analysis. *Information and Software Technology*, 2019. 108: p. 115-138.



- [25]. Jabeen, A. and S. Ranganathan, Applications of machine learning in GPCR bioactive ligand discovery. *Current Opinion in Structural Biology*, 2019. 55: p. 66-76.
- [26]. Xu, C. and S.A. Jackson, Machine learning and complex biological data. *Genome Biology*, 2019. 20(1).
- [27]. Zhang, Z. and E. Sejdić, Radiological images and machine learning: Trends, perspectives, and prospects. *Computers in Biology and Medicine*, 2019. 108: p. 354-370.
- [28]. Bock, F.E., et al., A review of the application of machine learning and data mining approaches in continuum materials mechanics. *Frontiers in Materials*, 2019. 6.
- [29]. Ekins, S., et al., Exploiting machine learning for end-to-end drug discovery and development. *Nature Materials*, 2019. 18(5): p. 435-441.
- [30]. Woldaregay, A.Z., et al., Data-driven blood glucose pattern classification and anomalies detection: Machine learning applications in type 1 diabetes. *Journal of Medical Internet Research*, 2019. 21(5).
- [31]. Najafzadeh, M. and A. Ghaemi, Prediction of the five-day biochemical oxygen demand and chemical oxygen demand in natural streams using machine learning methods. *Environmental Monitoring and Assessment*, 2019. 191(6).
- [32]. Singh, H., P.S. Rana, and U. Singh, Prediction of drug synergy in cancer using ensemble-based machine learning techniques. *Modern Physics Letters B*, 2018. 32(11).
- [33]. Choubin, B., et al., River suspended sediment modelling using the CART model: A comparative study of machine learning techniques. *Science of the Total Environment*, 2018. 615: p. 272-281.
- [34]. Zarkogianni, K., M. Athanasiou, and A.C. Thanopoulou, Comparison of Machine Learning Approaches Toward Assessing the Risk of Developing Cardiovascular Disease as a Long-Term Diabetes Complication. *IEEE Journal of Biomedical and Health Informatics*, 2018. 22(5): p. 1637-1647.
- [35]. Aram, F., et al., Design and validation of a computational program for analysing mental maps: Aram mental map analyzer. *Sustainability (Switzerland)*, 2019. 11(14).
- [36]. Asadi, E., et al., Groundwater Quality Assessment for Drinking and Agricultural Purposes in Tabriz Aquifer, Iran. 2019.
- [37]. Asghar, M.Z.; Subhan, F.; Imran, M.; Kundi, F.M.; Shamshirband, S.; Mosavi, A.; Csiba, P.; R. Várkonyi Kóczy, A. Performance Evaluation of Supervised Machine Learning Techniques for Efficient Detection of Emotions from Online Content. Pre-prints 2019, 2019080019 (doi: 10.20944/preprints201908.0019.v1).
- [38]. Bemani, A.; Baghban, A.; Shamshirband, S.; Mosavi, A.; Csiba, P.; Várkonyi-Kóczy, A.R. Applying ANN, ANFIS, and LSSVM Models for Estimation of Acid Sol-vent Solubility in Supercritical CO<sub>2</sub>. Preprints 2019, 2019060055 (doi: 10.20944/preprints201906.0055.v2).
- [39]. Mosavi, A., T. Rabczuk, and A.R. Varkonyi-Koczy, Reviewing the novel machine learning tools for materials design, D. Luca, L. Sirghi, and C. Costin, Editors. 2018, Springer Verlag. p. 50-58.
- [40]. Mosavi, A., et al., Prediction of multi-inputs bubble column reactor using a novel hybrid model of computational fluid dynamics and machine learning. *Engineering Applications of Computational Fluid Mechanics*, 2019. 13(1): p. 482-492.
- [41]. Mosavi, A. and A.R. Varkonyi-Koczy, Integration of machine learning and optimization for robot learning, R. Jablonski and R. Szweczyk, Editors. 2017, Springer Verlag. p. 349-355.
- [42]. Nosratabadi, S., et al., Sustainable business models: A review. *Sustainability (Switzerland)*, 2019. 11(6).
- [43]. Rezakazemi, M., A. Mosavi, and S. Shirazian, ANFIS pattern for molecular membranes separation optimization. *Journal of Molecular Liquids*, 2019. 274: p. 470-476.
- [44]. Riahi-Madvar, H., et al., Comparative analysis of soft computing techniques RBF, MLP, and ANFIS with MLR and MNLR for predicting grade-control scour hole geometry. *Engineering Applications of Computational Fluid Mechanics*, 2019. 13(1): p. 529-550.
- [45]. Shabani, S.; Samadianfard, S.; Taghi Sattari, M.; Shamshirband, S.; Mosavi, A.; Kmet, T.; R. Várkonyi-Kóczy, A. Modeling Daily Pan Evaporation in Humid Cli-mates Using Gaussian Process Regression. Preprints 2019, 2019070351 (doi: 10.20944/preprints201907.0351.v1).
- [46]. Shamshirband, S.; Hadipoor, M.; Baghban, A.; Mosavi, A.; Bukor J.; Annamaria R. Varkonyi-Koczy, Developing an ANFIS-PSO Model to predict mercury emissions in Combustion Flue Gases. Preprints 2019, 2019070165 (doi: 10.20944/preprints201907.0165.v1).
- [47]. Shamshirband, S., et al., Ensemble models with uncertainty analysis for multi-day ahead forecasting of chlorophyll a concentration in coastal waters. *Engineering Applications of Computational Fluid Mechanics*, 2019. 13(1): p. 91-101.
- [48]. Shamshirband, S., A. Mosavi, and T. Rabczuk, Particle swarm optimization model to predict scour depth around bridge pier. *arXiv preprint arXiv:1906.08863*, 2019.
- [49]. Torabi, M., et al., A Hybrid Machine Learning Approach for Daily Prediction of Solar Radiation, in *Lecture Notes in Networks and Systems*. 2019, Springer. p. 266-274.





- [50]. Choubin, B., et al., An ensemble prediction of flood susceptibility using multivariate discriminant analysis, classification and regression trees, and support vector machines. *Science of the Total Environment*, 2019. 651: p. 2087-2096.
- [51]. Dineva, A., et al., Multi-Label Classification for Fault Diagnosis of Rotating Electrical Machines. 2019.
- [52]. Farzaneh-Gord, M., et al., Numerical simulation of pressure pulsation effects of a snubber in a CNG station for increasing measurement accuracy. *Engineering Applications of Computational Fluid Mechanics*, 2019. 13(1): p. 642-663.
- [53]. Ghalandari, M., et al., Investigation of submerged structures' flexibility on sloshing frequency using a boundary element method and finite element analysis. *Engineering Applications of Computational Fluid Mechanics*, 2019. 13(1): p. 519-528.
- [54]. Ghalandari, M., et al., Flutter speed estimation using presented differential quadrature method formulation. *Engineering Applications of Computational Fluid Mechanics*, 2019. 13(1): p. 804-810.
- [55]. Karballaezadeh, N., et al., Prediction of remaining service life of pavement using an optimized support vector machine (case study of Semnan–Firuzkuh road). *Engineering Applications of Computational Fluid Mechanics*, 2019. 13(1): p. 188-198.
- [56]. Menad, N.A., et al., Modeling temperature dependency of oil - water relative permeability in thermal enhanced oil recovery processes using group method of data handling and gene expression programming. *Engineering Applications of Computational Fluid Mechanics*, 2019. 13(1): p. 724-743.
- [57]. Mohammadzadeh, S., et al., Prediction of Compression Index of Fine-Grained Soils Using a Gene Expression Programming Model. *Infrastructures*, 2019. 4(2): p. 26.
- [58]. Mosavi, A. and M. Edalatfar, A Hybrid Neuro-Fuzzy Algorithm for Prediction of Reference Evapotranspiration, in *Lecture Notes in Networks and Systems*. 2019, Springer. p. 235-243.
- [59]. Mosavi, A., A. Lopez, and A.R. Varkonyi-Koczy, Industrial applications of big data: State of the art survey, D. Luca, L. Sirghi, and C. Costin, Editors. 2018, Springer Verlag. p. 225-232.
- [60]. Mosavi, A. and T. Rabczuk, Learning and intelligent optimization for material design innovation, D.E. Kvasov, et al., Editors. 2017, Springer Verlag. p. 358-363.
- [61]. Bui, D.T., et al., Shallow landslide prediction using a novel hybrid functional machine learning algorithm. *Remote Sensing*, 2019. 11(8).
- [62]. Pham, B.T., et al., Landslide susceptibility modeling using Reduced Error Pruning Trees and different ensemble techniques: Hybrid machine learning approaches. *Catena*, 2019. 175: p. 203-218.
- [63]. Zhang, X. and S. Mahadevan, Ensemble machine learning models for aviation incident risk prediction. *Decision Support Systems*, 2019. 116: p. 48-63.
- [64]. Jaiswal, A. and R. Malhotra, Software reliability prediction using machine learning techniques. *International Journal of Systems Assurance Engineering and Management*, 2018. 9(1): p. 230-244.
- [65]. Khagi, B., G.R. Kwon, and R. Lama, Comparative analysis of Alzheimer's disease classification by CDR level using CNN, feature selection, and machine-learning techniques. *International Journal of Imaging Systems and Technology*, 2019.
- [66]. Kumari, M., et al., Comparative analysis of machine learning based QSAR models and molecular docking studies to screen potential anti-tubercular inhibitors against InhA of mycobacterium tuberculosis. *International Journal of Computational Biology and Drug Design*, 2018. 11(3): p. 209-235.
- [67]. Bataineh, A.A., A comparative analysis of nonlinear machine learning algorithms for breast cancer detection. *International Journal of Machine Learning and Computing*, 2019. 9(3): p. 248-254.
- [68]. Manzoor, S.I. and J. Singla, A comparative analysis of machine learning techniques for spam detection. *International Journal of Advanced Trends in Computer Science and Engineering*, 2019. 8(3): p. 810-814.
- [69]. Odugu, K. and B. Rajasekar, Comparative analysis on supervised machine learning models for future wireless communication networks. *International Journal of Innovative Technology and Exploring Engineering*, 2019. 8(6): p. 721-723.
- [70]. Hou, Q., et al., An adaptive hybrid model for short-term urban traffic flow prediction. *Physica A: Statistical Mechanics and its Applications*, 2019. 527.
- [71]. Du, P., et al., A novel hybrid model for short-term wind power forecasting. *Applied Soft Computing Journal*, 2019. 80: p. 93-106.
- [72]. Zhang, W., H. He, and S. Zhang, A novel multi-stage hybrid model with enhanced multi-population niche genetic algorithm: An application in credit scoring. *Expert Systems with Applications*, 2019. 121: p. 221-232.
- [73]. Pham, B.T. and I. Prakash, A novel hybrid model of Bagging-based Naïve Bayes Trees for landslide susceptibility assessment. *Bulletin of Engineering Geology and the Environment*, 2019. 78(3): p. 1911-1925.
- [74]. Wu, J., et al., A new hybrid model to predict the electrical load in five states of Australia. *Energy*, 2019: p. 598-609.



- [75]. Albalawi, F., et al., Hybrid model for efficient prediction of poly(A) signals in human genomic DNA. *Methods*, 2019.
- [76]. Gorczyca, M.T., N.C. Toscano, and J.D. Cheng, The trauma severity model: An ensemble machine learning approach to risk prediction. *Computers in Biology and Medicine*, 2019. 108: p. 9-19.
- [77]. Wang, Q.F., M. Xu, and A. Hussain, Large-scale Ensemble Model for Customer Churn Prediction in Search Ads. *Cognitive Computation*, 2019. 11(2): p. 262-270.
- [78]. Naghibi, S.A., et al., Application of rotation forest with decision trees as base classifier and a novel ensemble model in spatial modeling of groundwater potential. *Environmental Monitoring and Assessment*, 2019. 191(4).
- [79]. Ali, M. and R. Prasad, Significant wave height forecasting via an extreme learning machine model integrated with improved complete ensemble empirical mode decomposition. *Renewable and Sustainable Energy Reviews*, 2019: p. 281-295.
- [80]. Yamanaka, A., Y. Maeda, and K. Sasaki, Ensemble Kalman filter-based data assimilation for three-dimensional multi-phase-field model: Estimation of anisotropic grain boundary properties. *Materials and Design*, 2019. 165.
- [81]. Yadav, D.C. and S. Pal, To generate an ensemble model for women thyroid prediction using data mining techniques. *Asian Pacific Journal of Cancer Prevention*, 2019. 20(4): p. 1275-1281.
- [82]. Ardabili, S., Mosavi, A., Mahmoudi, Mesri Gundoshmian, T, Nosratabadi, S., Varkonyi-Koczy, A., Modelling temperature variation of mushroom growing hall us-ing artificial neural networks, *Preprints 2019*.
- [83]. Mesri Gundoshmian, T., Ardabili, S., Mosavi, A., Varkonyi-Koczy, A., Prediction of combine harvester performance using hybrid machine learning modeling and response surface methodology, *Preprints 2019*.
- [84]. Ardabili, S., Mosavi, A., Varkonyi-Koczy, A., Systematic review of deep learning and machine learning models in biofuels research, *Preprints 2019*.
- [85]. Ardabili, S., Mosavi, A., Varkonyi-Koczy, A., Advances in machine learning model-ing reviewing hybrid and ensemble methods, *Preprints 2019*.
- [86]. Ardabili, S., Mosavi, A., Varkonyi-Koczy, A., Building Energy information: demand and consumption prediction with Machine Learning models for sustainable and smart cities, *Preprints 2019*.
- [87]. Ardabili, S., Mosavi, A., Dehghani, M., Varkonyi-Koczy, A., Deep learning and machine learning in hydrological processes climate change and earth systems a systematic review, *Preprints 2019*.
- [88]. Mohammadzadeh D., Karballaezadeh, N., Mohemmi, M., Mosavi, A., Varkonyi-Koczy A., Urban Train Soil-Structure Interaction Modeling and Analysis, *Preprints 2019*.
- [89]. Mosavi, A., Ardabili, S., Varkonyi-Koczy, A., List of deep learning models, *Preprints 2019*.
- [90]. Nosratabadi, S., Mosavi, A., Keivani, R., Ardabili, S., Aram, F., State of the art sur-vey of deep learning and machine learning models for smart cities and urban sustainability, *Preprints 2019*.
- [91]. Perez, H.; Tah, J.H.M.; Mosavi, A. Deep Learning for Detecting Building Defects Using Convolutional Neural Networks. *Sensors* 2019, 19, 3556.