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Prediction of Two-Phase Flow Regime in Oil Wells Using Hybrid Models

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ABSTRACT

This study investigates the application of hybrid machine learning techniques, including boosting, bagging, voting, and stacking for flow regime prediction in two-phase vertical pipe flow. We propose a decision tree-based ensemble classifier utilizing algorithms like Random Trees (RT), J48, Reduced Error Pruning Trees (REPT), Logistic Model Trees (LMT), and Decision Trees with Naive Bayes (NBT).

The effectiveness of the chosen hybrid algorithm was assessed using a comprehensive suite of metrics, including classification accuracy, precision, recall, confusion matrix, F1-score, and PRC area. Our investigation revealed that ensemble methods, particularly boosting (AdaBoost, LogitBoost, MultiBoosting) and, achieved superior prediction accuracy compared to individual classifiers. Notably, MultiBoosting exhibited the most promising performance within the boosting category. These findings conclusively demonstrate the superiority of ensemble algorithms over single classifiers in predicting flow regimes. By leveraging this approach, the accuracy of flow regime prediction was demonstrably increased, reaching a level as high as 96%.

The study introduces a superior method for predicting two-phase flow regimes in vertical flows, achieving high accuracy and reducing complexity and cost, resulting in reliable results under various operating conditions.

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Introduction

The accurate prediction of two-phase flow regimes in vertical pipes remains a critical challenge across numerous industrial applications. While machine learning has emerged as a promising tool for this task, existing research has primarily focused on individual algorithms. This study aims to address a crucial gap in the current knowledge base by investigating the potential of ensemble classification techniques, particularly within the domain of tree-based models. By exploring hybrid machine learning approaches, this research seeks to significantly improve the effectiveness of predicting two-phase flow regimes in vertical pipes.

While machine learning approaches like neural networks, deep learning, and decision trees have demonstrated effectiveness in two-phase flow regime classification, the potential of ensemble hybrid models, particularly those constructed from tree-based learners, for achieving superior prediction accuracy remains largely unexplored, especially for vertical pipe configurations. This research aims to bridge this knowledge gap by investigating the efficacy of ensemble methods including boosting, bagging, and voting in improving the accuracy and reliability of two-phase flow regime predictions within vertical pipes.

This study holds significant practical value for industries dealing with two-phase flow in vertical pipes. The proposed method offers a robust and cost-effective solution for achieving highly accurate flow regime predictions, leading to improved efficiency and design optimization across various operating conditions. The aim of study is to explores the potential of leveraging ensemble hybrid machine learning, particularly tree-based models, to unlock superior accuracy in predicting two-phase flow regimes in vertical pipes. By harnessing this cutting-edge approach, we aim to revolutionize the reliability and generalizability of flow regime predictions across a wide range of industrial applications.

Literature Review

Recent advancements in machine learning have led to the development of novel methodologies for predicting multiphase flow regimes. These techniques play a crucial role in flow regime classification tasks, leveraging data generated from experimental databases (Table 1).

Table 1: Summary of Machine Learning Applications in Two-Phase Flow Regime Prediction

Ref	Technique	Application
[1]	Neural Networks	Vertical Two-Phase Flows
[2]	Deep Learning (FFT)	Flow Regime Classification
[3]	ANN	PEM Fuel Cell Flow Channels
[4]	Deep Learning Neural Networks	for flow pattern forecasting, Inclined Pipes (0-90°)
[5]	Decision Trees, SVM, ANN	Flow Regime Identification
[6]	ANN	Water Holdup Prediction
[7]	Neural Networks	Flow Regime Identification
[8]	Machine Learning (PDF & PSD)	Gas & Liquid Flow Rate Determination
[9]	MLP, RBF, PNN (ANNs)	Flow Pattern Recognition
[10]	SVM (with Electrical Capacitance Tomography)	Two-Phase Flow Regime Identification
[11]	ANN	Pressure Prediction (Multiphase Flows)
[12]	Gradient Boosting, RF, SVM	Flow Regime Classification
[13]	Two-Step Machine Learning	Flow Regime Identification (Helical Flows)
[14]	Various AI Models	Flow Pattern Classification (Gas-Liquid)
[15]	Classification Learner	Predict Flow Patterns Downstream of an Orifice
[16]	Neuro-Fuzzy System	Pressure Drop Prediction in Vertical Multiphase Flows
[25]	Self-Organized Neural Networks (SONN)	Local Flow Regime Mapping
[26]	ANN	Entrained Liquid Fraction Estimation
[27]	RF, LR, SVM, MLP	Flow Pattern Classification
[28]	Condivity signals and ANN	Flow Pattern Classification
[29]	Comparative Study (ML , DL)	Flow Regime Prediction
[30]	ANN	Flow Regime Classification (Gas-Liquid-Pulp)

Current research on machine learning for two-phase flow pattern identification in vertical pipes overlooks the potential benefits of ensemble classification techniques. This omission represents a critical gap that future studies should address.

Data Acquisition Preprocessing

This work utilized a dataset compiled from published literature, encompassing 2252 experimental data points [1]. These data points encompassed a wide range of flow regimes forecasted in relation to various input parameters. These parameters included temperature, pipe diameter. mixture type, surface tension (liquid and gas phases), superficial velocity (liquid (Vl) and gas(Vg)), viscosity, and density (liquid and gas). Feature importance analysis served as a guiding principle for selecting the most relevant input variables for model development. Table II summarizes the range of values for each feature. Furthermore, Figure 1 visually depicts the distribution of data points across the various flow regimes, bubble flow (BB), slug flow (SL), churn flow (CH), annular flow (AN), dispersed bubble (DB), semi-annular (SA), intermittent (IN), and elongated bubble (EB). Characterization of Database Input Features.

Table 2: Characterization of Database Input Features

Feature	Vg, m/s	VL, m/s	Temperature °C	Diameter (mm)
Maximum	99.80	4.14	35.	20.00
Minimum	0.02	0.002	19.8	5.500
Stand. Dev	13.70	0.61	2.91	3.17
Variance	187.68	0.37	8.46	10.04
mean	3.13	0.25	22.66	9.00

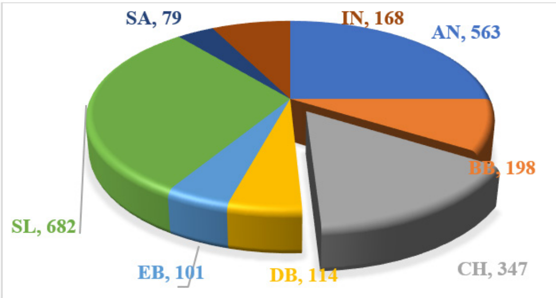


Figure 1: Distribution of Data Point by Flow Regimes

Ensemble Machine Learning Models

An approach called ensemble machine learning combines multiple base models to create an ideal predictive model [2]. Ensemble learning techniques can be divided into three categories: bagging, stacking, and boosting [3]. Averaging, bagging, random forest, stacking, and boosting are some of the most used ensemble techniques [4]. By developing advanced algorithms and generating results with a high degree of accuracy, ensemble approaches can aid in winning machine learning competitions. Averaging is utilized for regression, while voting is used for classification.

Machine learning competitions have witnessed the success of ensemble approaches, with winning solutions frequently incorporating them [5]. Notably, these competitions have seen the implementation of powerful collaborative filtering algorithms that leverage ensemble techniques.

This research explores the application of ensemble methods in enhancing the accuracy of machine learning models [6]. While countless model combination strategies exist, three primary ensemble learning techniques dominate real-world applications. These methods demonstrably improve model accuracy and performance. However, it is crucial to acknowledge the trade-off: increased complexity, potential for higher computational expense, and potentially less interpretable outputs compared to single models.

Building on the work of this study investigated the application of ensemble machine learning models for predicting two-phase flow regimes in vertical pipes [7]. The findings corroborated the notion that tree-based ensemble models offer superior robustness and achieve enhanced performance compared to single classifiers. These results support the growing consensus that ensemble methods hold significant promise for improved flow regime prediction accuracy.

Figure 2 presents a flowchart that outlines the key steps involved in developing a machine learning model for predicting two-phase flow regimes within vertical pipes [8]. We employ a diverse set of optimization techniques including Exhaustive Search (ES), Genetic Algorithm (GA), Greedy Stepwise Selection (GS), Particle Swarm Optimization (PSO), Random Search (RS), and Rank Search (RNS). The detailed results of applying these methods to J48, Random Trees (RT), Decision Tree Reduced-Error Pruning (REPT), Random Forests (RF), logistic model trees (LMT), and Decision Trees with Naive Bayes (NBT) classifiers on dataset-1.

This research addresses the challenge of imbalanced data in the modelling process. To mitigate this issue, we employ the Synthetic Minority Oversampling Technique (SMOTE). Unlike basic up-sampling, which merely replicates existing minority class instances, SMOTE generates synthetic data points. This approach fosters a more robust training dataset by interpolating between existing minority class samples, akin to data augmentation techniques commonly used in image recognition tasks.

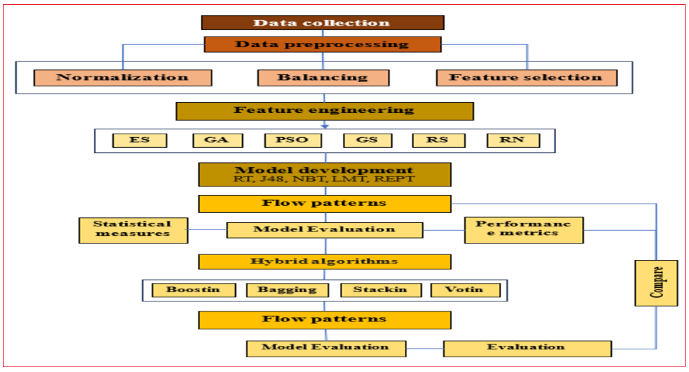


Figure 2: Methodology for Machine Learning Model Evaluation

Performing Data preprocessing

Crucially, following data loading, anomaly detection and treatment are paramount. Visualization techniques can be employed to identify data points exhibiting significant deviations from the anticipated range [9]. These outliers can be addressed through various strategies. Exclusion from the dataset is an option, but it's vital to consider the potential impact on sample size and generalizability. Alternatively, data imputation techniques can be utilized to replace outliers with values more aligned with the central tendency of the data. Once outliers are dealt with, data randomization is recommended. This mitigates potential biases introduced during data collection and ensures the representativeness of the sample for subsequent analyses. Finally, data normalization is crucial. This process scales the features within the dataset to a comparable range, facilitating more robust statistical analyses and model building.

Feature Selection

Feature selection play critical role in constructing robust machine learning models for prediction tasks. As Zheng and Casari (2018) pointed out, judicious selection of features can significantly enhance model accuracy [10]. Conversely, incorporating irrelevant or redundant features can negatively impact predictive performance [11]. In light of this, this section will delve into a comprehensive exploration of optimal input selection strategies specifically tailored for deep learning-based flow pattern prediction.

The development of high-performing ML models hinges on the effective identification of relevant features. Feature selection techniques play a critical role in this process, aiming to optimize the model by selecting a subset of features that are most informative and contribute most significantly to the learning task. This section delves into a comparative analysis of various optimization techniques employed for feature selection.

This study investigates the performance of various optimization algorithms for ML models. Optimization algorithm using different tree-models presented in Figure 3. CV and TR performance metrics are evaluated for each classifier-optimizer combination. Analysis of these tables reveals that GA, PSO, and RS generally outperform the other optimization methods when applied to the aforementioned classifiers on dataset-1.

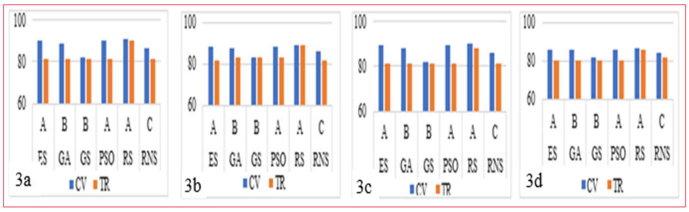


Figure 3: Comparison of Common Optimization Algorithm Using Different Tree-Models A- Rf Model; B- J48; C- Rt-Model; D-Rept Model

Figure 3 compares the effectiveness of various search methods for different machine learning models: RF, J48, RT, and REPT. The search methods include ES, GA, GS, PSO, RS, and RNS, and their effectiveness is measured by accuracy in both Cross-Validation (CV) and Training (TR) scenarios. For the RF model (figure3-a), RS and ES have the highest accuracy in both CV and TR scenarios, indicating that these search methods are effective in finding the optimal parameters for the RF model. GA and PSO also perform well, but GS and RNS have lower accuracy, suggesting that they may not be the best search methods for the RF model. For the J48 model, RS and ES again have the highest accuracy in the CV scenario, while GA and PSO have the highest accuracy in the TR scenario [12]. GS and RNS have lower accuracy in both scenarios, indicating that they may not be the best search methods for the J48 model (figure b). For the RT model, RS has the highest accuracy in both CV and TR scenarios, followed closely by ES and PSO in the CV scenario and GA in the TR scenario. GS and RNS have lower accuracy, suggesting that they may not be effective search methods for the RT model (figure c). For the REPT model (figure d), RS has the highest accuracy in the CV scenario, while ES and PSO have the highest accuracy in the TR scenario. GS and RNS have lower accuracy in both scenarios, indicating that they may not be the best search methods for the REPT model [13].

It can be concluded that, RS and ES are the most effective search methods for the RF, J48, and REPT models, while RS is the most effective search method for the RT model. GA and PSO are also effective for some models, but GS and RNS are generally not as effective [14]. These findings suggest that the choice of search method can significantly impact the accuracy of machine learning models, and that selecting the appropriate search method is crucial for optimizing model performance.

Discussing the Results

Evaluation Performance of Individual Models

Performance evaluation goes beyond just accuracy and incorporates additional statistical measures like root relative squared error (RRSE), kappa statistics, relative absolute error, mean square error (MSE), and root mean square (RMSE). Details for these measures for each model presented in Figure 4.

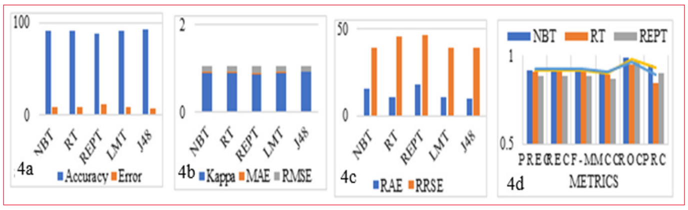


Figure 4: Performance of Flow Pattern Classification. A- Accuracy and Error; B- Kappa, Mae, Rmse; C- Rae and Rrse; D- Metrics

The results in the Figure 4 show the performance of various ML models in predicting two-phase flow regimes in vertical pipes. The models evaluated include NBT, RT, REPT, LMT and J48 (C4.5 Decision Tree). When comparing the performance of the models, the J48 decision tree model achieves the highest accuracy at 92.71%, the lowest error rate at 7.29% (Figure 4-a), and the highest Kappa statistic at 0.9159 (Figure 4-b), indicating excellent agreement between the predicted and actual classes. The J48 model also has the lowest MAE of 0.0215 and RMSE of 0.129, suggesting high precision in its predictions (Figure4-b). The NBT model also performs well, with an accuracy of 92.03%, error rate of 7.97%, and Kappa of 0.908. The LMT model is another strong performer, with an accuracy of 91.97%, error rate of 8.03%, and Kappa of 0.9074. In contrast, the REPT model has the lowest performance, with an accuracy of 88.82%, error rate of 11.17%, and Kappa of 0.8711. The RT model also has lower performance compared to the J48, NBT, and LMT models. Overall, the results suggest that the J48 decision tree model is the most effective in predicting two-phase flow regimes in vertical pipes, followed by the NBT and LMT models. The REPT and RT models show relatively lower performance compared to the other three models [15].

To assess the efficacy of various tree-based models in flow pattern classification, a comprehensive evaluation was conducted using six performance metrics: precision, recall, F1-score, Matthews correlation coefficient (MCC), area under the ROC curve (AUC), and area under the PRC curve. As depicted in figure 4-d, the J48 decision tree emerged as the superior model, achieving the highest values for all metrics except AUC, where the NBT model displayed a slight advantage. Notably, J48 exhibited a well-balanced performance across all metrics, demonstrating its overall effectiveness. Conversely, the REPT tree demonstrated the weakest performance among the evaluated models.

Performance Evaluation of Hybrid Machine Learning Models
To visualize the performance of the four hybrid machine learning models employed in this study Boosting, Bagging, Voting, and Stacking, Figure 5 depicts their accuracy and error rates.

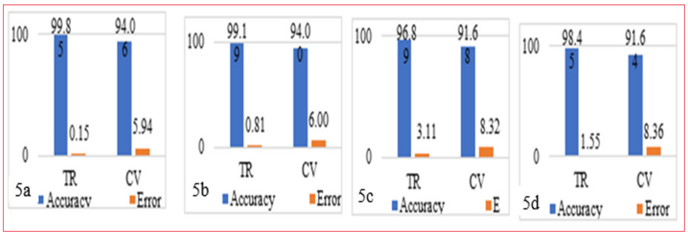


Figure 5: Hybrid Methods. a) Boosting; b) Bagging; c) Voting; d) Stacking

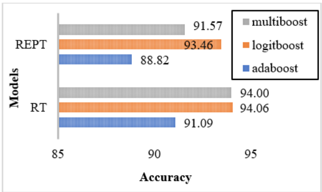
The models were assessed on two datasets: a training set and a cross-validation set. Among the evaluated models, boosting (Figure 5-a) emerged as the top performer with an average accuracy of 96.95% and an average error of 3.05%. Notably, on the training dataset, it achieved the highest accuracy (99.85%) and the lowest error (0.15%). Bagging secured the second position with an average accuracy of 96.59% and an average error of 3.41% (Figure 5-b). Its performance on the training dataset closely mirrored Boosting's results. However, on the cross-validation dataset, Bagging exhibited a slight decrease in accuracy (94.00%) and a corresponding increase in error (6%). Voting displayed a more consistent performance across both datasets (Figure 5-c). It achieved an average accuracy of 94.28% and an average error of 5.71%. While its training set performance (accuracy: 96.89%, error: 3.11%) was comparable to Boosting, the cross-validation set results (accuracy: 91.68%, error: 8.32%) revealed a slight decline. Stacking exhibited the lowest overall accuracy (95.04%) and the highest overall error (4.95%) among the tested models (Figure 5-d). While its training dataset performance remained acceptable (accuracy: 98.45%, error: 1.55%), it demonstrated a significant drop in accuracy (91.64%) and a rise in error (8.36%) on the cross-validation dataset, suggesting limitations in generalizability.

Investigation revealed that boosting emerged as the most effective hybrid approach within this study. This is evidenced by its achievement of the highest accuracy and the lowest error rate on both the training data and the cross-validation set. This superior performance suggests a strong generalization capability of the boosting algorithm, indicating its ability to perform well on unseen data. While bagging exhibited competitive performance, both voting and stacking algorithms displayed a noticeable decrease in accuracy when applied to the unseen data.

In order to graphically compare the performance of various boosting algorithms on the identical dataset, we can generate a plot depicting the relationship between model accuracy and algorithm type for REPT and RT models (Figure 6).

Results, as illustrated in Figure 6, demonstrate the comparative performance of various machine learning models in terms of accuracy. LogitBoost emerges as the most effective model, achieving an impressive accuracy of 94%. MultiBoost and adaboost follow closely behind, exhibiting accuracies of 93% and 91% respectively. Conversely, RT and REPT yielded the lowest accuracies within the tested models, scoring 86% and 87% respectively. It can be concluded that, the bar graph appears to show that Adaboost, Logitboost, and Multiboost are more accurate models than RT and REPT.

Figure 7 illustrates the comparative performance of various ensemble methods for flow pattern identification. The figure presents the distribution of accuracy metrics3 across eight distinct flow patterns, denoted by BB, SL, CH, AN, EB, DB, SA, and IN. Figure 7 demonstrates the effectiveness of ensemble models in flow classification. While they achieved good accuracy for SA, EB, BB, and IN flow regimes, SA, and DB flows showed lower performance. Churn flow exhibited the lowest accuracy. Our evaluation demonstrates impressive accuracy across all flow patterns, with most metrics surpassing a threshold of 0.9. This signifies the model's robust performance in handling diverse flow types. However, a closer examination reveals subtle variations in performance between patterns. Notably, the BB pattern achieves the highest precision, recall, and F1-measure, indicating the model's exceptional proficiency in this specific category. Conversely, the IN pattern exhibits the highest MCC, suggesting its potential strength in handling a different type of flow pattern. These observations imply the model might exhibit specialization towards certain flow patterns, warranting further investigation into the underlying factors influencing this behavior.



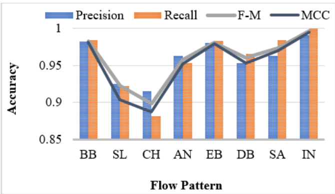


Figure 6: The Performance Boosting Approach Figure 7 Accuracy Measures Distributions for Different Flow Patterns

Confusion Matrix

The evaluation of hybrid models' performance can be further enhanced through the use of confusion matrices. Table 3 presenting a confusion matrix that details the performance of the voting ensemble classification model.

Table 3: Confusion Matrix of Flow Pattern Modelling Using Voting Hybrid Models

		Actual pattern							
		BB	SL	CH	AN	EB	DB	SA	IN
Predicted pattern	BB	365	11	0	0	0	0	0	2
	SL	7	568	34	9	3	14	2	1
	CH	0	34	267	15	0	0	3	0
	AN	0	6	7	359	0	0	8	1
	EB	0	2	0	0	397	5	0	0
	DB	0	13	0	0	9	420	0	0
	SA	0	1	3	10	0	0	301	0
	IN	2	0	0	1	0	0	0	333

Voting model demonstrated proficiency in correctly classifying instances belonging to classes BB and SL (Table 3). However, a closer examination reveals specific limitations. In some cases, the model misclassified 11 instances, assigning them to class SL when they genuinely belonged to class BB. Conversely, it failed to identify 7 instances of class SL altogether. Despite these classification errors, the model's overall performance appears satisfactory, as evidenced by high true positive rates for most classes. Nonetheless, it is crucial to acknowledge its challenges with certain classes, such as SA and IN, where it exhibits higher rates of both false positives and false negatives.

Conclusions

• This study provides compelling evidence that hybrid machine learning algorithms significantly outperform single classifiers in predicting two-phase flow regimes within vertical pipes. These hybrid models achieve remarkable accuracy, reaching up to 96%. This approach offers a robust and cost-effective method for achieving highly accurate flow regime predictions across a wide range of operating conditions.

• Beyond the superior accuracy, the study sheds light on crucial aspects of building effective models for this task. These insights include feature selection techniques, data preprocessing methods, and robust model performance evaluation strategies. The research findings hold significant value for researchers and engineers in the field of two-phase flow analysis. The proposed hybrid ensemble learning techniques offer a powerful toolkit for enhancing the accuracy and reliability of flow regime predictions. This, plays a critical role in optimizing process design, control, and safety across various industrial applications.

• This research establishes a strong foundation for the application of hybrid machine learning in predicting two-phase flow regimes within vertical pipes. Looking ahead, exciting prospects exist for further development. These advancements include improvements in model performance, optimization of hybrid architectures, and refined feature selection and data preprocessing techniques. Additionally, future research can address potential misclassifications and explore the expansion of these models to even more diverse operating conditions [16-30].

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