Enhancing Classification Accuracy in Two-Phase Pipe Flow with Novel Bio-Inspired Optimization-driven Neural Network

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Maintaining the effective and dependable functioning of manufacturing processes necessitates the precise recognition of two-phase flow in pipes. However, current classification techniques fail to achieve high accuracy due to the unpredictable and complex nature of flow. The intricate patterns and variances in flow's dynamics could be complex for conventional approaches to capture, resulting in inadequate achievement of classification. Therefore, it is imperative to create cutting-edge strategy that can successfully handle these issues and raise the precise classification of the two-phase pipe flow. In this article, a jellyfish search-driven augmented Hopfield neural network (JS-AHNN) is presented to address this problem. The suggested approach optimizes the framework of neural networks by making use of the durability and versatility of bio-inspired techniques, which enhances the performance of algorithm. We show that the suggested JS-AHNN methodology is more effective than traditional techniques at achieving higher accurate classification through comprehensive trials on acquired data samples. The experimental findings demonstrate the JS-AHNN superior performance compared to existing methods in terms of accuracy (95.3%), recall (96%), precision (95.6%), and f1 score (95.8%). The findings show that combination of neural networks and bio-inspired optimization improves the two-phase pipe flow classification efficiency, which advances dependable and effective industrial operations.

Keywords: Two-Phase Pipe Flow, Industrial Systems, Unpredictable Nature, Jellyfish Search-Driven Augmented Hopfield Neural Network (JS-AHNN).

1. Introduction

The two-phase pipe flow is a fascinating field that explores the complex interactions between two different fluid phases inside conduits in the complex field of fluid dynamics. When liquid and gas phases exist simultaneously, it is known as the two-phase flow phenomenon, and it offers both engineers and researchers a variety of opportunities and challenges. Fluid dynamics are seen in thermal management systems, oil and gas transportation, other manufacturing, environmental, and technological applications. Understand and categorize two-phase pipe flow to maximize system efficiency and ensure process safety and effectiveness [1, 2]. Two-phase pipe flow classification is the grouping patterns of flow, which has unique characteristics and contributing factors. The flow patterns, which depict the spatial and temporal distribution of both gases and liquids, offer an extensive comprehension of the fluid's dynamics in the pipe. Precise classification is important because it can provide insight into the underlying physics governing the flow, assisting in system analysis, design, and management [3, 4]. The inherent complexity caused by a variety of elements affecting the behavior of fluids is one of the main challenges in the classification of two-phase flows. Variables like fluid characteristics, flow rates, pipe geometry, and ambient conditions influence the wide range of observed flow patterns. To create an accurate and flexible classification system, professionals and experts need help to sort through the complexity [5, 6]. Technology increases the need for accurate and effective classification methods. Engineers and scientists operate to create robust models and tools that can detect two-phase pipe flow under different conditions. These classification systems help understand fluid behavior and develop specific solutions [7, 8]. Two-phase flow classification affects energy consumption, sustainability, and safety beyond technical details. Enhancing energy-intensive procedures by classifying and predicting flow patterns reduces operational costs and environmental impact. A comprehensive understanding of flow patterns improves safety protocols, ensuring systems can withstand and mitigate two-phase flow dynamics hazards [9, 10]. Phase dynamics and complex interactions lead to limited accuracy in forecasting the changes between flow patterns in two-phase pipe flow. The goal of this study is to improve the two-phase pipe flow classification accuracy using an innovative method that makes use of a novel bio-inspired optimization-driven neural network. This novel approach seeks to enhance the accuracy and consistency of classifying intricate fluid dynamics inside conduits by utilizing the effectiveness of biological principles.

2. Related works

According to the author of, [11] examined the two-phase flow pattern recognition and void fraction measurements separate the oil pipelines' scaling thickness of layer. Using an evaluation approach, they provided information about flow patterns and void fractions independent of layer thickness. The findings offered important details for two-phase flow system optimization. In [12] identified high-pressure two-phase flow regime transitions utilizing deep learning and image processing. They analyzed images using sophisticated techniques, identifying clear flow patterns. Their approach makes a significant contribution to the comprehension of complicated high-pressure two-phase systems by differentiating between flow regimes. Research [13] employed deep learning to predict the two-phase flow mechanisms fluids in upward-inclined pipes. The method forecasted intricate flow dynamics through the use of a neural network model. The findings demonstrated that deep learning can improve two-phase flow prediction in inclined pipes. A two-phase method for recognizing flow regimes utilising machine learning and liquid-phase velocity data was presented in the [14]. They aimed to categorize two-phase system flow regimes by using an innovative methodology. The technique displayed encouraging results in obtaining accurate flow regime identification, improving our comprehension of intricate fluid dynamics.

Author [15] examined the use of machine learning to forecast two-phase flow patterns and offered creative methods to improve prediction accuracy. They provided essential insights for enhanced modeling and comprehension of two-phase flows by demonstrating the identification of patterns in complex flow scenarios using a variety of datasets and algorithms. The study [16] investigated the potential of artificial intelligence and time-domain feature extraction techniques for improving the efficiency of two-phase flow meters that used the gamma-ray absorption method. They focussed on these methods could be used to increase two-phase flow measurement accuracy and dependability, which could lead to significant developments in flow metering technology. Research [17] presented a unique method for classifying two-phase flow patterns using machine learning and void fraction time series. They investigated the dynamic behavior of void fractions to improve the precision of flow pattern identification. The outcomes highlighted the suggested method was effective in categorizing two-phase flow patterns. The model for steady-state multiphase pipe flow presented in the [18] used machine learning techniques on lab data. The developed model effectively predicts the behavior of multiphase flows, providing valuable insights for applications in the oil sector and other fields. Study [19] presented a lattice Boltzmann model based on phase fields that can be used to simulate liquid, gas, and solid flows. The model allowed for the efficient simulation and analysis of intricate interactions between gases, fluids, and solids in a variety of flow scenarios by incorporating a phase-field approach within the lattice Boltzmann framework. Research [20] focused on using ultrasonic phased array technology to identify two-phase flow regimes. They utilized an innovative method to describe flow patterns, offering significant contributions to the fields of instrumentation and flow measurement. By using ultrasonic phased array techniques, their research advances the comprehension of two-phase flow dynamics.

The research elements could be categorized: The approaches are discussed in Section 2. The experiment's findings are presented in Section 3. The last section of this research, section 4, is the conclusion.

3. Methodology

3.1 Dataset

A collection of flow pattern data [21] from experiments base $[PTM + 12]$ was made up of the most significant investigations conducted in the field. Mainly for this investigation, this data set was selected from the available sets because it has a lot of information points (5676), a extensive range of angles of inversion$(-90^{\circ}\ to\ 90^{\circ})$, and 2 pipe sizes ($ID = 1/2\ in\ and\ 1/4$ in), as well as the variety of patterns flow seen at all pipe inversion angles. The study takes into consideration the following flow patterns such as stratified smooth (SS), stratified wavy (SW), intermittent (I), bubble (B), scattered bubble (DB), and annular (A). Slug (SL) and Churn are taken into the intermittent flow pattern (CH) flow pattern in combination $[PTM + 12]$. For evaluating the algorithm's performance, three tests are suggested. Test 1 requires consideration of each recommended flow pattern. Test 2 stratifies the flow ST $(ST = SS + SW)$ by combining the$SS\ andSW$ data points. Test 3 integrate the distributed patterns flow $(DB + B)$ and the separated patterns flow$(ST + A)$.

3.2 Jellyfish Search-Driven Augmented Hopfield Neural Network (JS-AHNN)

Two-phase pipe flow can be effectively classified using the Jellyfish Search-Driven Augmented Hopfield Neural Network (JS-AHNN). This novel method combines AHNN with jellyfish search principles, showing improved flow phase discrimination accuracy. In complex pipe flow systems, the JS-AHNN model presents a promising approach for precise classification.

3.2.1 Jellyfish Search Algorithm

The Jellyfish search technique, which enhances parameters for accurate phase recognition and flow characterization, effectively classifies two-phase pipe flow. The Jellyfish Search Optimization (JSO) technique is a metaheuristic algorithm that derives its inspiration from the behavior of jellyfish. The following sequence of operations represents the method by which jellyfish search for food:

- The behavior of the individual jellyfish within the swarm.
- Water circulation is used as a driving force to produce the jellyfish bloom.
- The movements of jellyfish in the sea can be found here. It utilizes a method known as JSO. Requires into consideration the following set of idealized principles.
- The time control procedure is responsible for coordinating the transition between the two advanced motions. The movements of jellyfish, specifically the motions that take place within the swarm, follow the flow of the ocean.
- Jellyfish are more likely to collect in places where there is a substantial quantity of food easily accessible.
- The amount of food that can be found is determined by the location and the function that is associated with the aim.

3.2.2 Augmented Hopfield Neural Network (AHNN)

The two-phase pipe flow method of classification is improved by the Augmented Hopfield Neural Network (AHNN) by adjusting weights to achieve better flow characterization and accurate phase identification. There are two types of neurons present in an augmented Hopfield network, discrete neurons and continuous neurons. Both types of neurons are present in the network. The discrete neurons utilize the discrete transfer operation known asg_c, which can be represented as in Equation (1-2):

$$v_{dij} = g_c(v_{dji}) = 1, if\ v_{dji} > 0 \quad (1)$$

$$v_{dji} = g_c\left(u_{dji}\right) = 0, if\ u_{dji} < 0 \quad (2)$$

No change in $v_{dji}, if\ u_{dji} = 0$ (3)

Where both input and output will be considered discrete neurons, d_{ji} are denoted by the symbols u_{dji}andv_{dji}, respectively. The Sigmoid transfer function g_c is utilized by continuous neuron types.

$$v_{cji} = g_c\left(v_{cji}\right) = \frac{1}{2} + (1 + \tan\lambda\, v_{cji})) \quad (4)$$

Where$u_{ij}$and v_{cij} represents input and output will be considered of the continuous neuronc_{ji}, respectively, and is a factor of scaling that is referred as the slope. Every neuron has called an input bias, simplified I_{dji} for discrete neuron d_{ji}In addition to I_{cji}, which stands for continuous neuron c_{ji}. It is determined that the conventional connection matrix S is utilized, which provides all neurons with a connection, both continuous and discrete. As an illustration, $t_{dji\to cmn}$is the link that leads from the discrete neuron, denoted by the d_{ji}, to the constant neuron, denoted by the cmn. Despite this, a recently discovered type of connection (in the form of a matrix W) between pairs of neurons. It illustrates the connection from neuron to $w_{ji\to mn}$ as follows: neuron pair $ckm\ dkm$ derived from pair$c_{ji}d_{ji}$.

Equation (3) and Equation (4) define the dynamics of the augmented model.

$$\frac{dU_{cji}}{dt} = \sum_{m,n} S_{cmn\Rightarrow cji} V_{cmn} + \sum_{m,n} S_{dmn-cji} V_{dmn} + I_{cji} + \sum_{m,n} W_{mn\to ji} V_{dmn} V_{dji} V_{cmn} \quad (5)$$

$$U_{dji} = \sum_{m,n} S_{cmn\to dji} v_{cmn} + \sum_{m,n} T_{dmn\to dji} V_{dmn} + I_{dji} + \sum_{m,n} W_{m,n\to ij} V_{cmn} V_{dmn} V_{cji} + \frac{1}{2} T_{dji\to dji}\Psi + \frac{1}{2} W_{ji\to ji} V^2{}_{cji}\Psi \quad (6)$$

Whereas$\Psi = -1. if\ V_{dji} = 1$, and $\Psi = 1.\ \ if\ V_{dji} = 0$

As illustrated, sequential updating of discrete neurons decreases the energy function Equation (5) due to system dynamics Equation (3) and Equation (4). First, analyze the change rate. Energy function affected by continuous neuron outputc_{ji} in Equations (7-9)

$$\frac{dF}{ds} = -\sum_{l,n} S_{dmn\to dji}\left(U_{dmn}\frac{cU_{dji}}{ds}\right)$$

$$-\sum_{l,n} S_{cmn\to dji}\left(U_{cmn}\frac{cU_{dji}}{ds}\right)-J_{dji}\frac{cU_{dji}}{ds}$$

$$-\sum_{l,n} X_{ln\to ji}\left(U_{cji}U_{cmn}U_{dmn}\frac{cU_{dji}}{ds}\right) \quad (7)$$

$$\frac{dF}{ds}=-\left(\frac{cU_{dji}}{ds}\right)\left(\sum_{l,n} S_{dmn\to dji}U_{dmn}+\sum_{m,n} S_{cmn\to dji}U_{cmn}+J_{dji}+\sum_{l,n} X_{mn\to ji}U_{cji}U_{cmn}U_{dmn}\right) \quad (8)$$

$$=-\left(\frac{d_f(V_{dji})}{ds}\right)\left(\frac{d_x(V_{dji})}{ds}\right) \quad (9)$$

The monotonic growing $g_c$makes this always nonpositive. Consider energy shift from discrete neuron d_{ji}changing state at iteration n, as indicated in below in Equation (10-12).

$$=-\left(\frac{dg_c}{dv_{cji}}\right)\left(\frac{dv_{cji}}{dt}\right)^2 \quad (10)$$

$$\Delta U_{cji}=0 \Longrightarrow \Delta \mathrm{F}=0 \quad (11)$$

If otherwise definedΨ

$$\Delta \mathrm{U_{cji}}=\Psi \quad \text{if}\, \Delta \mathrm{U_{cji}} \neq 0 \quad (12)$$

This number is always negative, according to logic similar to that Equation (2). Energy function Equation (5) cannot increase. This demonstrates that the system searches for the lowest possible energy functions Equation (5). Further establishes the validity of using genuine discrete neurons in the Hopfield system for augmented reality significant consequences for combined integer programming. The connected gradient network is similar to the upgraded Hopfield network that has been introduced. Neurals possessing Sigmoid nonlinearity in a connected gradient network symbolized discrete variables consisting of the reduced integrity constraints. The outputs of these continuous neurons were thresholder to produce distinct outcomes upon network convergence. Representing an augmented Hopfield discrete neurons and variables network was demonstrated above without having to give in to computational limitations compromising integrity. A accurate version is recommended to represent integer variables more effectively.

The Jellyfish Search-Driven Augmented Hopfield Neural Network (JS-AHNN) is a new way to sort two-phase flow in pipe systems. This model uses both Hopfield neural networks and jellyfish search optimization to make the classification process more accurate. The JS-AHNN performs well with complicated dynamics and suggests an effective method to improve classification in situations with two-phase pipe flow. Algorithm 1 displays the Jellyfish Search-Driven Augmented Hopfield Neural Network (JS-AHNN) for two-phase flow in pipe systems.

Algorithm 1: (JS-AHNN)

```
classHopfieldNetwork: def _init__(self, num_neurons) : self.num_neurons = num_neurons
```

```
self. weights = initialize_weights ()
definitialize_weights (self): pass
defupdate_neuron_state (self, input_pattern): pass
defjellyfish_search (problem): pass
classTwoPhasePipeFlowProblem:
def __init__(self, parameters):  pass
defevaluate_solution (self, solution):  pass
defhybrid_algorithm (pipe_flow_problem, hopfield_network, num_iterations):
for iteration in range (num_iterations):
solution_candidate = jellyfish_search (pipe_flow_problem)
energy_before = hopfield_network. evaluate_solution (solution_candidate)
hopfield_network. update_neuron_state (solution_candidate)
energy_after = hopfield_network.evaluate_solution (solution_candidate)
ifenergy_after<energy_before:
accept_solution (solution_candidate)
```

4. Result and Discussions

The process of classifying two-phase pipe flow using the hybrid Jellyfish Search-Driven Augmented Hopfield Neural Network (JS-AHNN) in Python involves developing the network architecture, integrating the Jellyfish search algorithm, and training on relevant data. For best results, uses a machine with a minimum of 16GB RAM, make sure it is compatible with Python 3.8, and use at least 8GB RAM.

In a two-phase pipe flow classification model, accuracy is defined as the percentage of cases that are correctly classified. It is the proportion of phases that were accurately predicted in all instances. Loss, which is usually cross-entropy, measures how far the model deviates from the actual labels. Its goal is to reduce mistakes made during training to increase accuracy. High accuracy and low loss values point to a well-performing model that successfully separates the gas and liquid phases in two-phase pipe flow classification. Figure 1 shows the outcome of accuracy and loss.

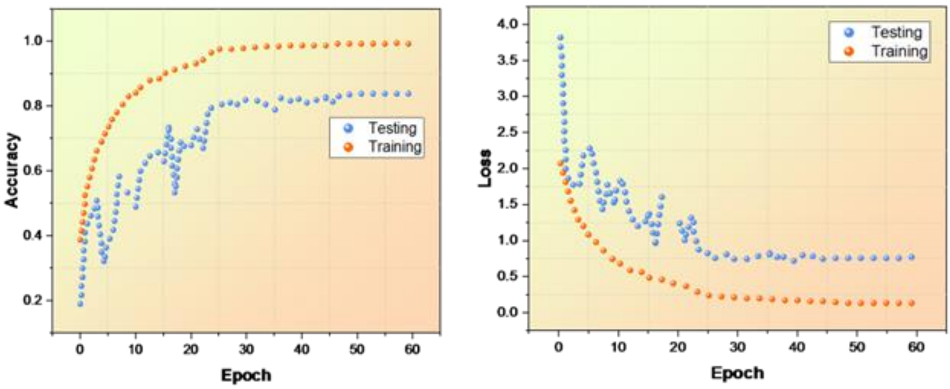

Figure 1: Outcome of accuracy and loss (Source: Author)

The efficiency of the suggested technique was compared with existing methods, such as extreme gradient boosting (XGBoost), random forests (RF), and multi-layer perceptron (MLP) [22]. The proposed and existing methods were assessed for accuracy, recall, precision, and f1 score.

Accuracy: Accuracy in the two-phase pipe flow classification is a metric used to evaluate a classification model's performance. The ratio of predicted instances to all of the dataset's instances is known as accuracy. The following Equation (13) can be used to determine the accuracy of a classification problem involving in two-phase flow.

$$Accuracy = \frac{TP+TN}{FP+FN+TP+TN} \quad (13)$$

❖ TP is the quantity of actual positives: The positive occurrences that were predicted.

❖ TN is denoted by the total amount of real negatives: The adverse events that were accurately forecast.

❖ FP as the number of false positives: Positive cases that weren't predicted correctly.

❖ FN is the number of false negatives: The number of negative cases that were inaccurately predicted.

Figure 2 and Table 1 depict the accuracy values. Our suggested method, JS-AHNN, outperformed existing methods with an accuracy of 95.3%, greater than XGBoost (94.9%), MLP (93.5%), and RF (91.6%). The findings offer the significant advancements in classification in two-phase pipe flow achieved by JS-AHNN compared to existing methods.

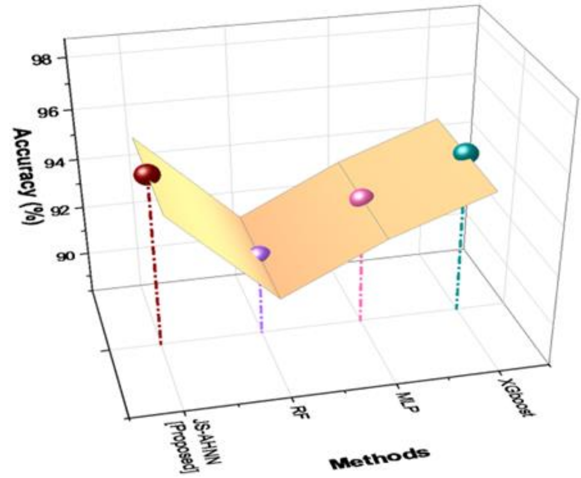

Figure 2: Outcome of accuracy (Source: Author)

Precision: Precision in two-phase pipe flow categorization measures the categorization model's efficiency. The proportion of actual positive forecasts to model positive forecasts is precision. It's crucial when utilizing unbalanced datasets, where one class (like one phase of a two-phase flow) is more prevalent. The following Equation (14) can be used to determine the precision of a classification problem involving in two-phase flow.

$$Precision = \frac{TP}{TP+FP} \quad (14)$$

Figure 3 and Table 1 depict the precision values. Our proposed approach, JS-AHNN, outperformed existing methods with aprecision of 95.6%, higher than XGBoost (93.2%), MLP (91.7%), and RF (90.2%). The results highlight the significant advancements in classification in two-phase pipe flow achieved by JS-AHNN compared to conventional methods.

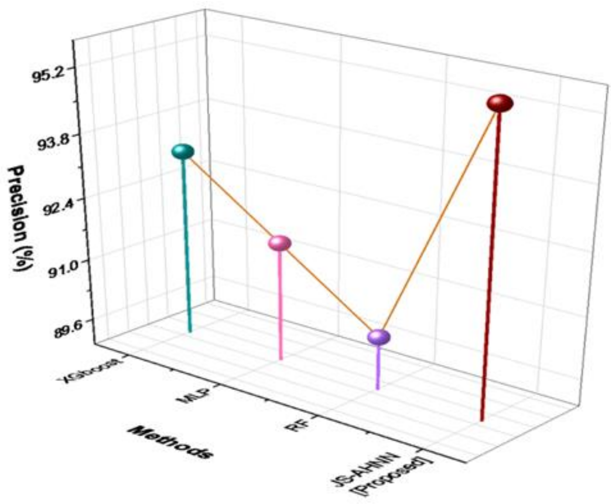

Figure 3: Outcome of precision (Source: Author)

Table 1: Performance evaluation of accuracy and precision (Source: Author)

Methods	Accuracy (%)	Precision (%)
XGboost	94.9	93.2
MLP	93.5	91.7
RF	91.6	90.2
JS-AHNN [Proposed]	95.3	95.6

Recall: Recall is a metric used to assess a classification model's performance in two-phase pipe flow classification. Recall measures explicitly a model's capacity to identify every pertinent instance of a given class accurately, it is also referred as sensitivity or true positive rate. Using the Equation (15), determine the recall.

$$Recall = \frac{TP}{TP+FN} \tag{15}$$

Figure 4 and Table 2 depict the recall values. Our proposed approach, JS-AHNN, outperformed existing methods with a recall of 96%, higher than XGBoost (95%), MLP (90%), and RF (91%). The results highlight the significant advancements in classification in two-phase pipe flow achieved by JS-AHNN compared to conventional methods.

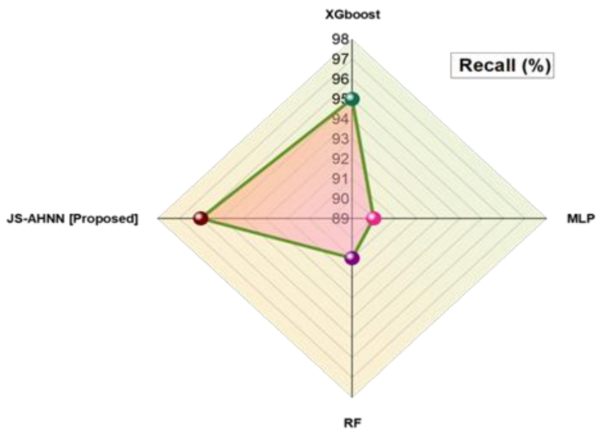

Figure 4: Outcome of recall (Source: Author)

F1 score: The F1 score is calculated by taking the harmonic mean of the two variables: recall, which is the proportion of true positive predictions to all actual positives, and precision, which is the proportion of true positive predictions to all predicted positives. For an f1 score, use this Equation (16):

$$F1\ score = \frac{2*(precision*recall)}{precision+recall} \tag{16}$$

Figure 5 and Table 2 depict the f1 score values. Our proposed approach, JS-AHNN, outperformed existing methods with anf1 score of 95.8%, higher than XGBoost (94.2 %), MLP (91.2%), and RF (90.1%). The results highlight the significant advancements in classification in two-phase pipe flow achieved by JS-AHNN compared to conventional methods.

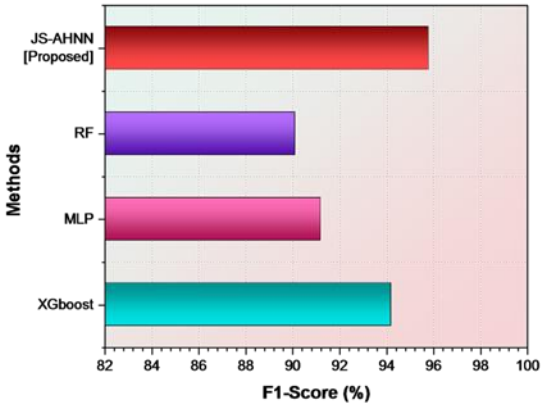

Figure 5: Outcome of f1 score (Source: Author)

Table 2: Performance evaluation of recall and f1 score (Source: Author)

Methods	Recall (%)	F1 score (%)
XGboost	95	94.2
MLP	90	91.2
RF	91	90.1
JS-AHNN [Proposed]	96	95.8

5. Conclusion

The accurate and effective operation of manufacturing processes depends on the precise identification of two-phase flow in pipes. The complexity and unpredictability of these flows provide difficulties for conventional categorization algorithms, which results in less than ideal accuracy. To overcome these difficulties, this paper suggests an innovative technique called the Jellyfish Search-driven Augmented Hopfield Neural Network (JS-AHNN). Through the utilization of bio-inspired methodologies, JS-AHNN enhances the neural network architecture, augmenting its robustness and adaptability. They demonstrate, using extensive experiments on collected data samples that JS-AHNN performs better than conventional methods, attaining more accuracy in the two-phase pipe flow classification. The experimental findings demonstrate the JS-AHNN superior performance compared to existing methods in terms of accuracy (95.3%), recall (96%), precision (95.6%), and f1 score (95.8%). The outcomes demonstrate that neural networks and bio-inspired optimization operate together, providing a viable approach to improve industrial processes' accuracy and dependability. The study's limitations include adapting and generalizability issues due to bio-inspired optimization understanding models. Different datasets and optimization strategies could be explored in future research to ensure robustness and applicability across two-phase pipe flow settings.

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