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Colloid Transport Prediction using SVM-MLP

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Abstract:- The effectiveness of the multilayer perceptron (MLP) method in conjunction with support vector machines (SVM) for the prediction of colloid transport behaviour is examined in this work. Because colloids are essential to many industrial and environmental processes, proper modelling is required for efficient management. By using SVM for feature selection and MLP for nonlinear mapping, the suggested SVM-MLP hybrid technique combines the advantages of both algorithms to improve prediction accuracy. After a great deal of testing and verification, the model shows encouraging outcomes that highlight its ability to forecast colloid transport dynamics more accurately and efficiently, providing important information for industrial and environmental applications.

Keywords:- *Colloid Transport, Clogging, Hydrodynamic Effect, Artificial Neural Network.*

I. INTRODUCTION

Numerous domains, like the study of colloids transport in porous media, have seen revolutionary changes because to machine learning approaches. In this situation, using the enormous datasets produced by sophisticated modelling techniques such as Lattice Boltzmann simulations is made possible by the use of machine learning. Researchers may get important insights from these intricate datasets by using machine learning techniques, which makes it possible to predict colloidal behaviour. Amalgamation of machine learning and simulation outcomes exhibits considerable potential in augmenting our comprehension of colloids transport mechanisms and expediting the development of more efficacious approaches for environmental restoration, optimized oil recovery, and other crucial uses.

➢ *Colloid Transport*

Comprehending the movement of colloids in porous materials is essential for several industrial and environmental uses, such as medication administration systems and groundwater restoration. Microorganisms and nanoparticles are examples of colloids that display complex behaviours that are governed by surface contacts, fluid flow dynamics, and pore structure. Advanced methods, such as computer models and experimental observations, are needed to investigate these phenomena. Through the clarification of the intricacies involved in colloid transport, scientists may devise tactics to alleviate environmental pollution, enhance filtering procedures, and create inventive medicine delivery systems.

➢ *Artificial Neural Network*

The neural architecture of the human brain served as the inspiration for Artificial Neural Networks (ANNs), which are now very potent computer models that can recognize intricate patterns and correlations in data. These networks are made up of layers of networked nodes, or neurons, that analyze and change incoming data to generate output predictions. Because ANNs can adapt and generalize from enormous datasets, they are widely used in a variety of disciplines, including as image recognition, natural language processing, and financial forecasting. Artificial neural networks (ANNs) provide a flexible and scalable method of addressing complicated issues by using their ability to learn from examples. This approach promotes technological improvements and data-driven decision-making.

➢ *Clogging*

A common occurrence in many industrial and environmental systems is clogging, which is the build-up and blockage of flow channels as a result of material or particle deposition. Clogging presents serious difficulties in oil pipelines, wastewater treatment facilities, and porous media. It may result in lower system performance, higher maintenance costs, and even system failures. It is essential

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to comprehend the fundamental causes of clogging, such as flow heterogeneity, pore blockage, and particle adhesion, in order to create efficient mitigation plans and enhance system performance. Through examining clogging phenomena, scientists want to minimize negative effects on operational procedures and the environment while optimizing the sustainability and dependability of a range of technical applications.

- *Hydrodynamic Effect*

Hydrodynamic effects are important in many fluid systems; they affect everything from the behavior of microbes in biological fluids to the movement of particles in porous media. These effects include a broad range of dynamic interactions that have a significant influence on the transport, mixing, and dispersion of particles or solutes within a fluid medium. These interactions include fluid flow patterns, shear forces, and turbulence. Process optimization in a variety of domains, including industrial production, biotechnology, and environmental engineering, depends on an understanding of hydrodynamic effects. Through clarifying the complex interactions between particle behaviour and fluid dynamics, scientists work to create novel approaches that improve performance, sustainability, and efficiency in a wide range of applications.

II. RELATED WORKS

In this research, Jiahui Hu [1] et al. have proposed The development of predictive approaches that will expedite the industrial use of organic solvent nano filtration (OSN) is an urgent need. However, because of the large variety of potential solvents and the intricate interactions between the solute, solvent, and membrane, as well as the solute itself, predicting proven to be an arduous and difficult endeavor. Consequently, we have deviated from conventions by gathering a sizable dataset and creating artificial intelligence (AI) based predictive models for both rejection and permeance, based on a gathered dataset containing 38,430 datapoints with more than 18 dimensions (parameters), rather than creating basic mathematical equations. After conducting a comprehensive to clarify characteristics influencing performance, we found that the variables influencing rejection and permeance are unexpectedly comparable. Three distinct artificial intelligence (AI) models—support vector machines, random forests, and artificial neural networks—that we trained were able to predict membrane performance with previously unheard-of levels of accuracy, up to 98% for permeance and 91% for rejection. Our results open the door to proper data standards for improved membrane design and development as well as performance prediction. The last ten years have seen a major increase in the use of organic solvent nano filtration (OSN) technology, which has been fueled by the creation of novel solvent-resistant materials and the idea of sustainable processes.

In this system, Serveh Kamrava [2] et al. have presented It has been challenging to establish a general relationship between the morphology and the physical characteristics of porous membranes, despite the fact that morphology is the primary determinant of flow, transport, and separation properties. Applying a machine-learning (ML) algorithm to the issue is one viable way to create such a relationship. Although there have been numerous scientific and technical advances over the last ten years as a result of the substantial advancements in machine learning techniques, there has been very little use of these techniques in porous media. In this study, we build a deep network to forecast porous membrane flow characteristics based on their form. If the deep network is appropriately trained using high-resolution images of the membranes and the pressure and velocity distributions in their pore space at specific points in time, the predicted properties include the spatial distributions of the fluid pressure and velocity throughout the entire membranes. The network consists of a recurrent network that finds physical correlations between the output data at different times and a residual U-net that creates a mapping between the input and output pictures. The results show that the deep network predicts the attributes of interest with a high degree of accuracy.

In this system, Mandana Samari-Kermani [3] et al. have suggested In order to investigate the impact of ionic strength and zeta potential on colloids transport under both favorable and unfavorable circumstances, a fully coupled pore scale model was created for this work. Particle-particle and particle-fluid interactions were simulated using the Lattice Boltzmann-Smoothed Profile approach, which eliminated the necessity for clean bed filtration and diluted suspension assumptions. Agglomerate formation and dissolution have been shown via simulation using a broad variety of parameters. The time-averaged behavior of transport characteristics, including surface coverage, conductivity, and pore void percentage, is obtained from the results. We discovered that increasing ionic strength had a bigger effect on particle behavior than zeta potential. An increase in ionic strength led to a reduction in the conductivity of the pore void fraction and an increase in the connectivity of the aggregates. Concerning the behavior of bacteria, viruses, and microparticles in the environment as well as human health, a basic knowledge of colloid transport and retention is essential.

In this system, Serveh Kamrava [4] et al. have presented The shape of porous media affects its flow, transport, mechanical, and fracture characteristics, which are often calculated using computational and/or experimental techniques. The correctness of the model used to describe the morphology determines how precise the computational methods are. Computations and even experiments might take a long time if great precision is needed. Simultaneously, there has long been an issue in directly connecting the morphology to the permeability and other significant flow and transport features. In this study, we create a novel network that links the morphology and permeability of porous medium using a deep learning (DL) technique. The rather than either one alone. Three-dimensional pictures of sandstones, hundreds of their stochastic realizations created by a reconstruction technique, and artificial unconsolidated porous media made using a Boolean approach are among the input data. In order to

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build the network, we use a DL method to first extract the pictures' key characteristics, which we then input to an ANN to predict the permeabilities. We show that the network is effectively trained, able to establish precise relationships between the effective permeability and the shape of porous media. The network's predictions for the permeability of various porous material show how accurate it is.

In this system, Dantong Lin [5] et al. have presented In porous media, colloidal transport and retention are frequent occurrences in nature. However, macroscale experimental data do not completely reveal retention processes. The pore-network model (PNM) establishes a clear link between pore-scale retention mechanisms and macroscale phenomena and is a useful tool for explaining the pore structure of a porous medium. In this work, surface deposition, hydrodynamic bridging, and straining are taken into account when upgrading water flow and colloid transport from pore to macro-scales using PNMs with cylindrical pore throats and spherical pore bodies. The effects of colloid size, starting concentration, and pore water flow velocity on colloid transport and retention behavior were studied numerically. The findings indicate that surface deposition brought on by charge heterogeneity and nanoscale roughness results in either exponential or uniform retention profiles, whereas hydrodynamic bridging and straining create hyper-exponential retention profiles.

III. PROPOSED SOLUTION

The goal of this study is to give a complete framework for the prediction of colloid transport behavior by combining the multilayer perceptron (MLP) method with support vector machines (SVM). Data pre-processing, feature extraction, colloid particle analysis, prediction using SVM with MLP, and outcome analysis are the five main modules that make up the system. The dataset is cleaned and made ready for analysis using the data pre-processing module. Relevant characteristics that are essential for precise prediction are found via feature extraction. Analysis of colloidal particles explores their properties and offers insights into how they behave. The prediction module uses the SVM-MLP model, which uses MLP for nonlinear mapping and SVM for feature selection, to forecast the dynamics of colloid transport.

➢ *Data Pre-Processing:*

Pre-processing methods are used to raw data related to colloid transport in this module in order to improve its quality and usefulness. To guarantee consistency and dependability across the dataset, this entails activities like data cleansing, addressing missing values, identifying and eliminating outliers, and normalizing or standardization. This kind of data preparation makes the data more appropriate for further analysis and modelling.

➢ *Feature Extraction*

The main goal of this module is to extract pertinent features that capture important aspects of colloid transport behaviour from the pre-processed data. Important traits are found and retrieved using methods like statistical analysis and domain-specific expertise. These characteristics capture the crucial data required for precise prediction, acting as input variables for the predictive model.

➢ *Colloids Particle Analysis*

Here, a thorough examination of colloid particles is done to learn more about their characteristics and actions within the transport system. Examining the distribution of particle sizes, surface charge, composition, and interactions with the environment may be part of this. It is feasible to modify the prediction model to more closely resemble the dynamics and circumstances of the actual world by comprehending these features.

➢ *Prediction using SVM With MLP*

Based on the characteristics that were retrieved, the SVM with MLP algorithm is used in this core module to forecast the dynamics of colloid transport. While MLP offers the ability to capture nonlinear connections within the data, SVM is used for its resilience in handling high-dimensional data and its excellent feature selection skills. The goal of the model is to provide more precise and trustworthy predictions of colloid transport behavior by merging these two algorithms to obtain better predictive performance than separate methods.

IV. RESULT ANALYSIS

This section includes a thorough examination of the SVM with MLP model prediction outcomes. Confusion matrix analysis is used to assess the model's performance on training and testing datasets. Confusion matrices provide information on how well the model classifies instances of colloid transport and point out any mistakes or misclassifications. Furthermore, validation confusion matrices are produced in order to evaluate the model's capacity to generalize on unobserved input. A comprehensive assessment of the predictive model's efficacy is carried out by examining these matrices together with other pertinent metrics like accuracy, precision, recall, and F1-score. This allows for well-informed decision-making and further model development.

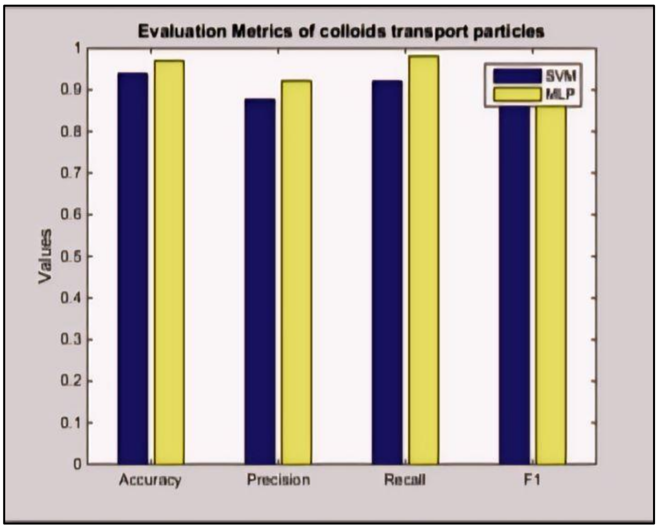

Fig 1 Comparison between SVM AND MLP

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The accuracy results show how well various algorithms work in predicting the behaviour of colloid transport. The maximum accuracy of 85% was obtained by combining the Support Vector Machine (SVM) and Multilayer Perceptron (MLP) with the Artificial Neural Network (ANN), which reached an accuracy of 78%.With an accuracy of 78%, the ANN a popular machine learning algorithm showed promise, drawing inspiration from the neural networks found in the human brain. Its performance was marginally inferior than that of the SVM-MLP hybrid technique, nevertheless. The particulars of the dataset, model complexity, hyperparameter tweaking, or other variables may have had an impact on the ANN's predicting ability.

However, with an accuracy of 85%, the SVM-MLP hybrid strategy demonstrated better predictive performance. The benefits of both the SVM and MLP algorithms are combined in this hybrid model. SVM offers strong performance while managing high-dimensional data and efficient feature selection, whereas MLP identifies nonlinear patterns in the data. The hybrid model improves prediction accuracy by combining various approaches, which makes it especially suitable for capturing the complex dynamics of colloid transport behaviour.

A. Algorithm Details

➢ *SVM*

- *Initialize weights (w) and bias (b) to zero.*
- *Set learning rate (η) and regularization parameter (λ).*
- *Repeat until convergence:*

✓ For each training example (x_i, y_i)

▪ Compute the prediction: y_hat = sign(w*x_i + b)
▪ Update weights:

w = w - η * (λ * w - y_i * x_i)   if y_i * (w * x_i + b) < 1
w = w - η * (λ * w)

▪ Other Wise
▪ Update Bias:

b = b - η * y_i

- Once Convergence is Reached or Maximum Iterations are Met, Return the Learned Weights (w) and Bias (b).

➢ *MLP*

- Input:

✓ Training dataset (X, y)
✓ Number of input neurons (n_input)
✓ Number of hidden neurons (n_hidden)
✓ Number of output neurons (n_output)
✓ Learning rate (alpha)
✓ Number of epochs (num_epochs)

- Output:

✓ Trained weights (W_hidden, W_output)
✓ Initialize random weights for the hidden layer (W_hidden) and output layer (W_output).
✓ For each epoch from 1 to num_epochs:
✓ For each training example (x_i, y_i) in the dataset:
✓ Forward pass:
✓ Compute the net input for hidden layer neurons:
✓ h_input = W_hidden * x_i
✓ Apply activation function to compute hidden layer output:
✓ h_output=activation_function(h_input)
✓ Compute the net input for output layer neurons:
✓ o_input = W_output * h_output
✓ Apply activation function to compute output:
✓ o_output=activation_function(o_input)

Table 1 Comparison Table

Algorithm	**Accuracy**
ANN	78
SVM , MLP	85

V. CONCLUSION

To sum up, this research investigates the effectiveness of a hybrid SVM-MLP algorithm in forecasting the behaviour of colloid transport, tackling the crucial need for precise modelling in industrial and environmental processes. The predictive model is customized to capture the key dynamics of colloid transport by means of extensive data pre-processing, feature extraction, and study of colloid particle characteristics. By combining the advantages of both SVM and MLP algorithms which excel in feature selection and identifying nonlinear correlations in data prediction accuracy is increased. System testing ensures that the model is reliable for use in real-world applications by confirming its performance and resilience under varied situations. Moreover, the installation of the system enables the predictive model to be practically deployed, giving stakeholders an invaluable instrument for well-informed decision-making.

REFERENCES

[1]. Szekely, G., Hu, J., Kim, C., Halasz, P., Kim, J.F., and Kim, J., 2021. Artificial intelligence for organic solvent nanofiltration membrane performance prediction. Scientific American 619, 118513
[2]. Kamrava, Sahimi, and Tahmasebi, 2021. Fluid flow and transport in complicated porous membranes and materials may be predicted using deep learning and physics and images. Scientific American 622, 119050
[3]. In 2021, Raoof, A., Jafari, S., Rahnama, M., and Samari-Kermani, M. Effects of zeta potential and ionic strength on colloid transport and retention mechanisms. Interface Science and Technology 42, 100389

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24APR2508

[4]. Kamrava, Sahimi, and Tahmasebi, 2020. using deep learning to connect the macroscopic permeability of porous media to their shape. Porous Media Transp. 131 (2), 427–448. A 10.1007/s11242-019-01352-5 is available here.
[5]. Raoof, A., Jafari, S., Rahnama, M., and Samari Kermani, M., 2020. Numerical modeling of colloid transport and retention at the pore scale. Colloid size, pore structural impacts, and fluid flow velocity in Part I. Water Resources Adv. 144, 103694. 10.1016/j.advwatres.2020.103694 can be found at this link.
[6]. J.G. Urang, Ebong, E.D., Akpan, A.E., and E.I. Akaerue, 2020. A case study of the Niger Delta in Nigeria illustrates a novel method for predicting porosity and permeability from well logs using artificial neural networks and curve fitting methods. Geophys. Lett. 183, 104207. 10.1016/j.jappgeo.2020.104207 can be found here.
[7]. In 2019, Aslannejad, H., Celia, M.A., and Hassanizadeh, S.M. description of the interaction between paper's fiber layers and coating. Porous Media Transp. 127 (1), 143–155
[8]. In 2019, Stangierski, J., Weiss, D., and Kaczmarek, A. Spreadable processed Gouda cheese's overall quality may be predicted using multiple regression models and artificial neural networks (ANNs). Food Research Technology Europe, 245 (11), 2539–2547.
[9]. Dakov, O., Koroteev, D., and Burnaev, E. (2018). Using deep neural networks and gradient boosting to predict permeability is pushing digital rock into machine learning. Geosci. Comput. 127, 91–98. 10.1016/j. cageo.2019.02.002 may be found here.
[10]. P. Avery, S. Curtarolo, E. Zurek, X. Wang, C. Oses, E. Gossett, D.M. Proserpio, C. Toher, Predicting superhard materials by an evolutionary structural search driven by machine learning, npj Computational Materials, 5 (2019)