# Scour Depth Estimation Around Hydraulic Structure Using Soft Computing Techniques

## FYUP Final Report

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## Abstract:

Scour depth estimation around hydraulic structures is a critical concern in civil engineering, with direct implications for the safety and integrity of infrastructure near water bodies. This research project employs soft computing techniques to develop two distinct predictive model for scour depth.

The project adopts a comprehensive approach, commencing with data collection, pre-processing, and feature engineering. Two robust soft computing models are developed utilizing real-world data on hydraulic structures, flow characteristics, sediment properties, and their corresponding scour depths: one for clear-water scouring and another for live bed scouring. The accuracy and performance of the models are rigorously evaluated through validation, employing industry-standard metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

The study delves into optimization techniques, such as genetic algorithms, to enhance the model's predictive capabilities. Furthermore, the project aims to visualize and interpret results effectively, facilitating clear communication of findings.

Ultimately, this research endeavours to provide a valuable tool for hydraulic engineers and infrastructure planners, aiding in predicting and mitigating scour depth around hydraulic structures. It offers insights into the potential of soft computing techniques in addressing complex challenges within civil engineering, contributing to the advancement of both the field and the safety of critical infrastructure.

*Keywords: Scour depth estimation, hydraulic structures, soft computing, predictive model, civil engineering, clear-water scouring, live bed scouring, optimization, validation, infrastructure safety.*

## 1. Introduction:

In this comprehensive study, we delve into the intricate phenomenon of scouring around bridge piers, a paramount concern in civil engineering. Scouring, a process triggered by the movement of bed sediment around bridge piers, occurs due to flow acceleration and the formation of vortices caused by the obstruction of these piers. Numerous researchers have investigated the underlying mechanisms behind scouring, focusing on the pivotal role of vortices in sediment entrainment.

The challenge of local scour, which includes clear-water scouring (CWS) and live-bed scouring (LBS), presents significant hurdles in bridge design and stability. While solutions like embedding bridge piers deep into the bed are financially burdensome, scour protection devices aim to resist flow and prevent vortex sinking and rising, thus ensuring the safety and efficiency of bridges. Incidents of bridge collapse resulting from pier settlement underscore the pressing need for precise scour depth estimation.

In this paper, we conduct a meticulous analysis of CWS and LBS around bridge piers, drawing from extensive field data. To predict the maximum scour depth crucial for economic viability and safe bridge pier design, we employ various soft computing techniques such as Artificial Neural Network (ANN) and Support Vector Machine (SVM). Two distinct models for CWS and LBS have been developed using different kernel functions, and a comprehensive comparison between these models has been executed.

Our study encompasses a diverse range of datasets sourced from field observations, and we utilize the gamma test (GT) to identify the most suitable input combinations for accurate scour depth predictions. By merging both laboratory and field data, this research offers a robust and nuanced understanding of scouring around bridge piers, providing valuable insights for the development of effective mitigation strategies and enhancing the overall safety and resilience of bridge infrastructure.

## 2. Literature Review:

In hydraulic engineering, scour depth prediction techniques have advanced significantly in recent years. Pioneering studies, such as those by Nil et al. (2023) and Choi and Choi (2022), used Support Vector Machines (SVM) to accurately predict scour-depth, demonstrating machine learning's potential in addressing complex scour phenomena. Further advancements came from Choudhary (2021) and Qaderi et al. (2021), who developed sophisticated Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Genetic Expression Programming (GEP) models, respectively. These models proved invaluable in enhancing the precision of scour depth predictions, particularly in dynamic and varied hydraulic conditions.

Additionally, researchers like Pandey (2020) and Saleh et al. (2019) focused on refining existing equations and identifying efficient parameters. Pandey's work involved the development of new K-factors tailored for Melville and Coleman's equation, ensuring better prediction accuracy. Saleh et al. delved into Genetic Expression Programming (GEP) models, pinpointing essential parameters for precise scour depth estimations.

The application of hybrid models has been pivotal, as seen in the work of Sreedhara et al. (2019), who utilized Particle Swarm Optimisation (PSO-SVM) to capture the intricate dynamics of scour processes. These models, combining optimization techniques and machine learning algorithms, have significantly improved the accuracy and reliability of scour depth predictions.

Furthermore, empirical validation studies conducted by Chavan et al. (2018) and Karimi et al. (2017) played a crucial role. Their experiments provided real-world data, essential for validating the predictive models and ensuring their applicability in practical scenarios.

It is also essential to acknowledge the foundational contributions of earlier researchers. The pioneering work of Kothyari et al., (1992), Chiew (1984), Qadar (1981), and Laursen (1963) laid the groundwork, establishing fundamental principles for understanding scour mechanisms. Their studies serve as bedrock knowledge upon which contemporary research builds, ensuring a comprehensive and evolving understanding of scour depth prediction. These collective efforts represent a significant stride in ensuring the safety and stability of bridges across various hydraulic and sedimentary conditions.

## 3. Research Gaps:

- Existing research has focused on developing empirical methods to forecast scouring around bridge piers. However, when dealing with the dynamic behaviour of scouring induced by various unknown causes, these calculations frequently need to be revised. As a result, depending simply on empirical calculations, it fails to analyse the scouring phenomenon appropriately.
- While some academics have investigated the application of soft computing approaches, such as Choi and Choi (2022) and Nil et al., (2023), their investigations have been limited in scope. They concentrated primarily on datasets with homogenous gravel and cylindrical pier types, ignoring the wide range of materials and pier shapes observed in real-world circumstances. As a result, there still needs to be a significant study gap in understanding the complex scouring dynamics, mainly when different materials and pier layouts are considered.

## 4. Objectives:

- **Prepare a Robust and Dynamic Dataset:** A crucial task is to curate a dynamic dataset that incorporates non-uniform particle sizes and diverse pier types. The dataset will be thoroughly filtered and cleaned using multiple data processing techniques, confirming its trustworthiness and suitability for inclusion into the predictive models under development.

- **Develop Predictive Models for Scour Depth:** The primary goal of this research is to employ soft computing techniques leveraging real-world data on hydraulic structures, flow patterns, sediment properties, and scour depths. Through the collection and processing of this data, the objective is to create robust predictive models for CWS and LBS scour depth around hydraulic structures.

- **Assess Model Accuracy and Performance:** Another key objective is to evaluate the accuracy and performance of the predictive models rigorously. This assessment will be validated using industry-standard metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

## 5. Methodology

- **Data Collection and Pre-processing**: In this first step, we collected extensive experimental data on clear water and live bed scouring, covering various scenarios and conditions. We identified and chose relevant variables influencing clear water and live bed scouring based on domain knowledge and a literature review. We divided the collected data into two groups: training data for model development and testing data for model evaluation.

- **Model Creation**: In this step, we developed an Artificial Neural Network (ANN) and a Support Vector Machine (SVM). Using the training data, we built the ANN model, focusing on layers, neurons, and activation functions in the network architecture. To enhance the ANN's performance, we utilized techniques such as cross-validation. Simultaneously, we constructed an SVM model using the same training data, fine-tuning parameters like the kernel function and regularization parameters through grid search and cross-validation.

- **Model Evaluation and Improvement**: we assessed the models' performance on the validation dataset using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics. We conducted a detailed error analysis to understand the models' strengths and weaknesses, refining them based on insights from error patterns. The refinement process involved adjusting hyperparameters, modifying features, and employing advanced techniques to improve accuracy.

- **Comparison and Best Model Selection**: we retrained the refined ANN and SVM models with the new parameters and tested them on new data. We compared their performance for clear water and live bed scouring scenarios using metrics like MAE and RMSE. The best models, with the lowest MAE and RMSE values on the testing data, were selected for predicting clear water and live bed scouring.

Throughout the systematic processes of data analysis, model creation, evaluation, and refinement, we ensured the selection of the most accurate models for predicting clear water and live bed scouring.

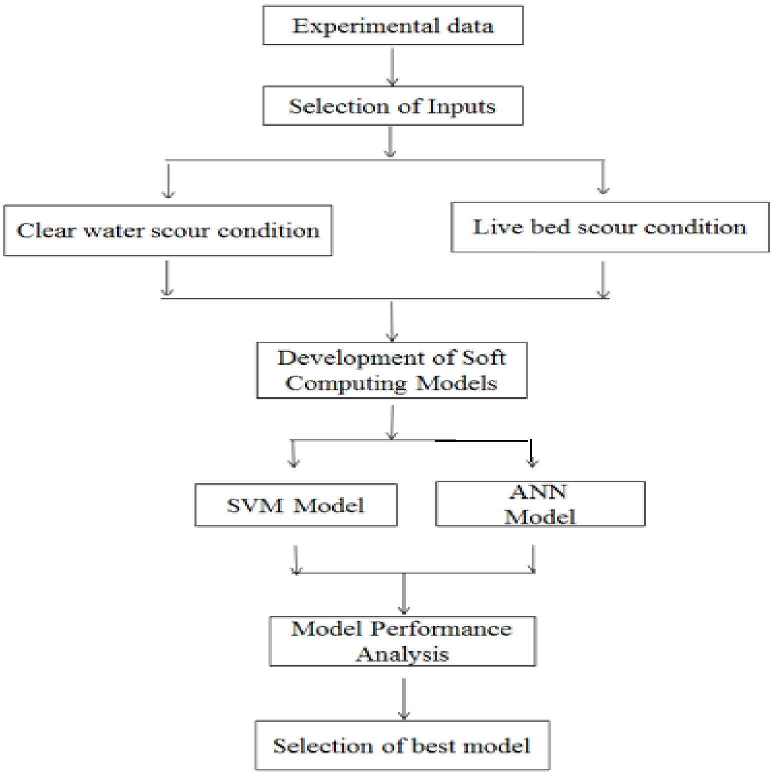
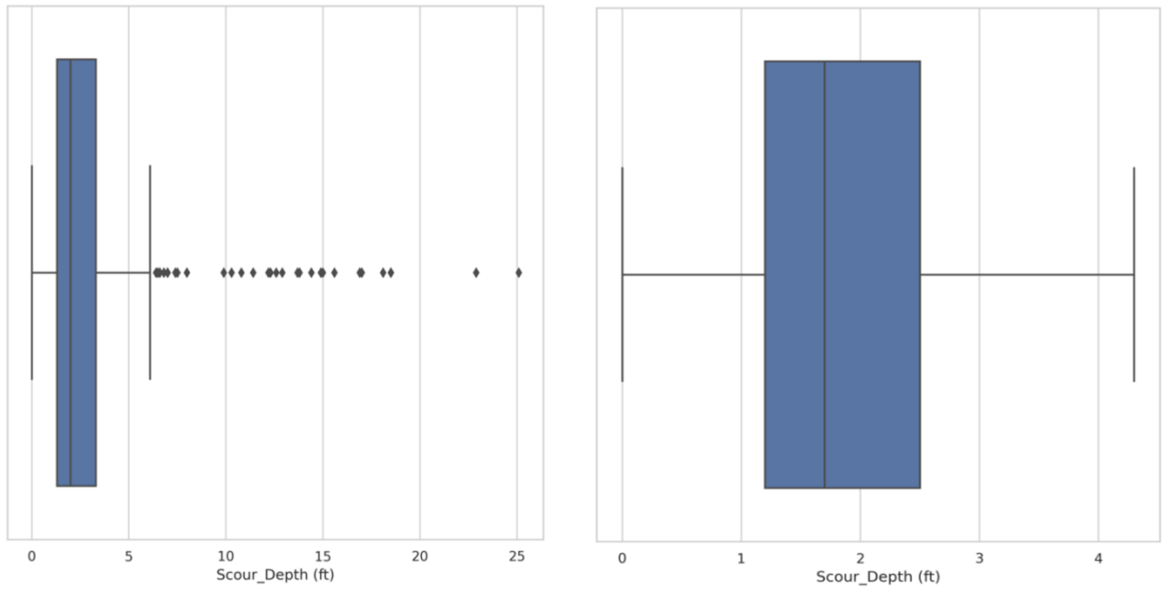


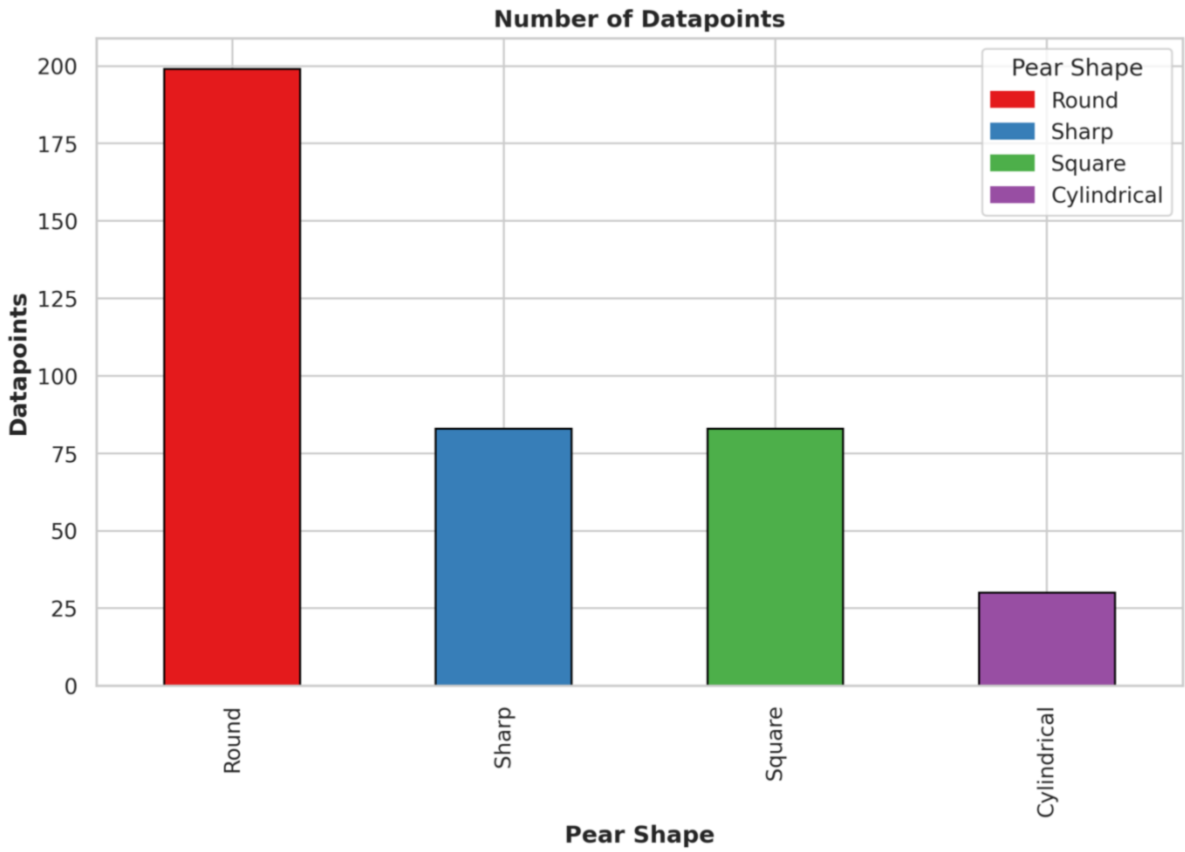

***Figure 1:*** *Flowchart for the overall methodology used in the project*

# 6. Results & Discussion

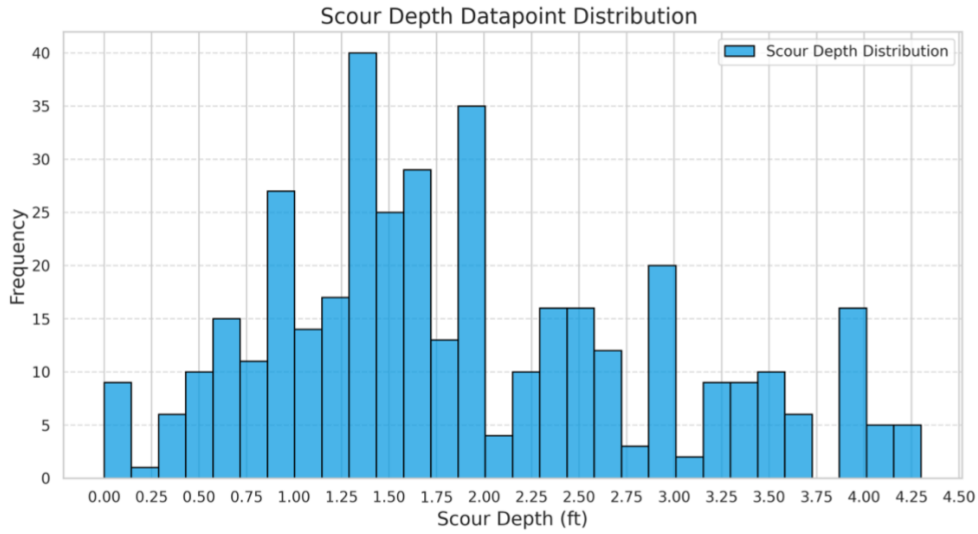



(a) (b)

***Graph 1: a)*** *Dataset including outliers. b) Dataset excluding outliers*



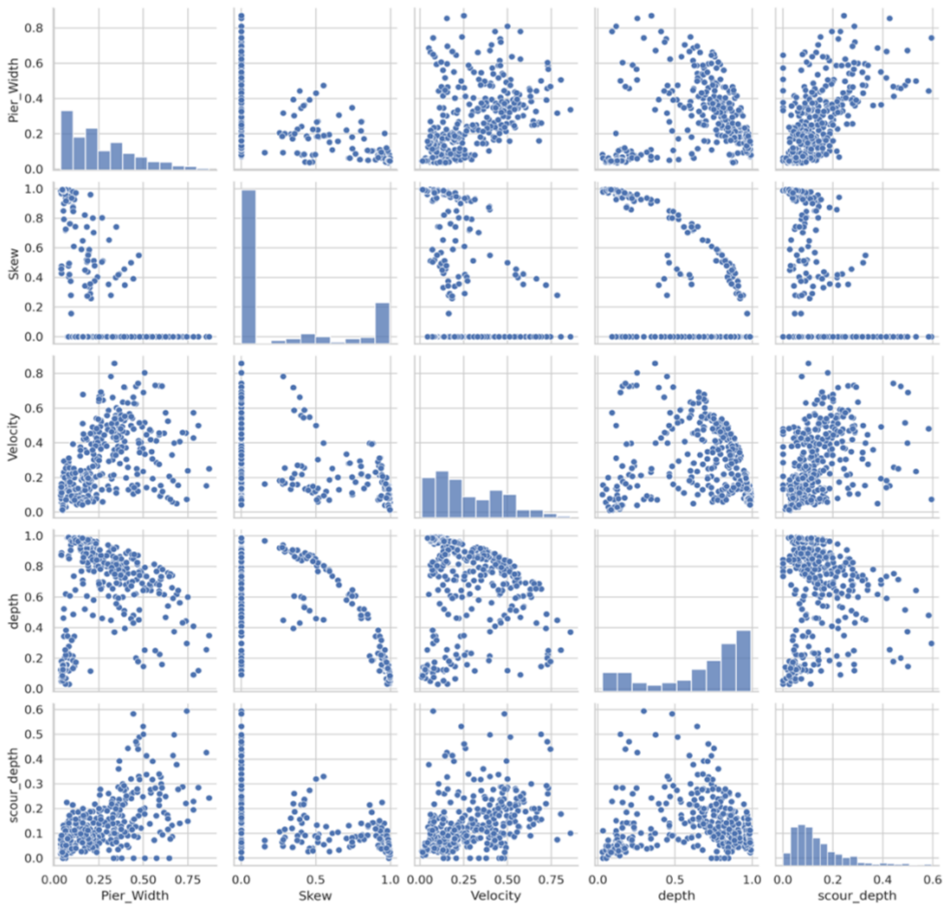

***Graph 2:*** *Number of datapoints and the shape of bridge pier*




***Graph 3:*** *Scour depth datapoints frequency distribution*

**Feature(Numeric) correlation after data normalisation**

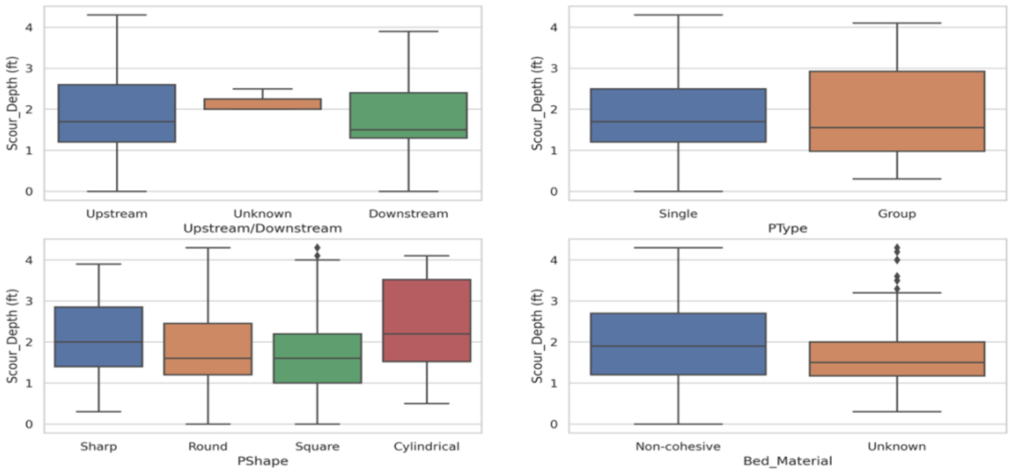
- Scour depth have some positive correlation with Pier width, velocity ,Depth.
- Scour Depth have very insignificant negative correlation with Skew.




***Graph 4:*** *Feature correlation after data normalisation*

**Feature(Nun - Numeric) correlation**

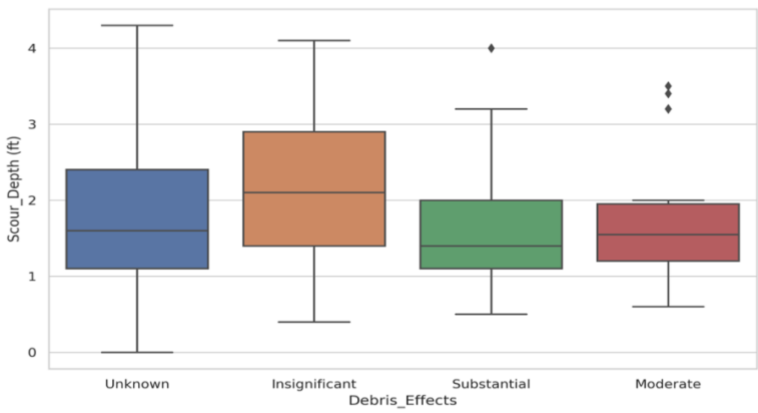
- Scour Depth doesn't have any effect based on current as both upstream and downstream have almost similar distribution.
- Pier Type seems to have impact on Scour depth as can be seen from boxplot 2.
- Pier shape looks to have impact on scour depth pier with shape of round and sharp have almost same distribution.
- Bed material seems to have strong impact on scour depth.




***Graph 5:*** *Non – numeric feature effect on scour depth*

**Debris Effect**

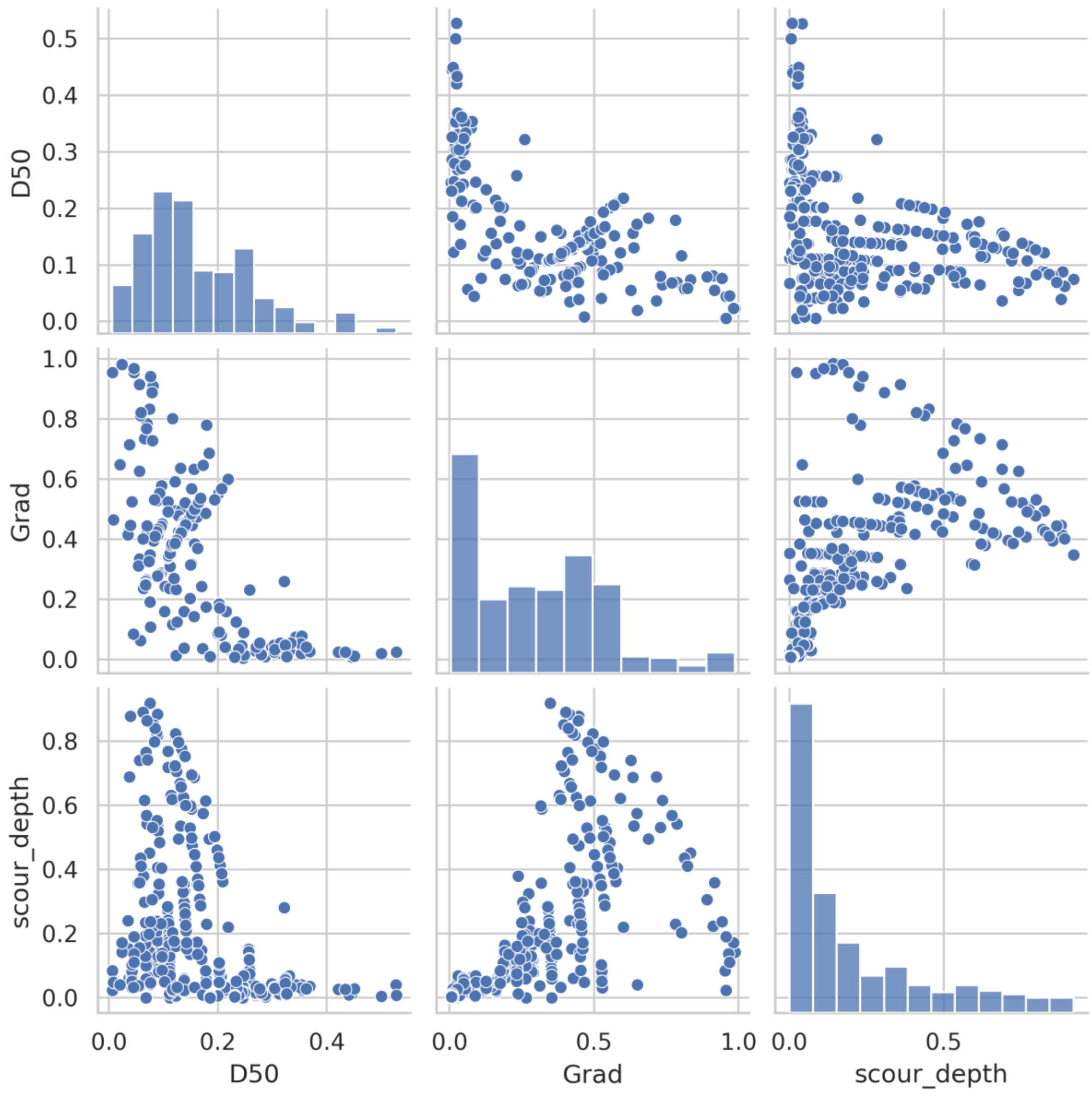
- Dataset with unknown values seam no harm as they almost distributed across entire range of scour depth values.
- Debris effect seems to increase from insignificant to substantial to moderate scour depth converges to a range of 0.2-0.6




***Graph 6:*** *Debris effect on scour depth*

**D50, Grad, Scour depth Correlation after normalisation**

- D50 have negative correlation with scour depth.
- Grad have significantly high correlation value.




***Graph 7:*** *D50, Grad, Scour depth Correlation (Normalised)*

**Dummy variables for the categorical feature**

Dummy variables are created to convert categorical data into a format that can be provided to machine learning algorithms to improve predictions or to include categorical data in statistical models.

***Table 1:*** *Dummy variables for the categorical feature*

| S.No. | Dummie Features |
|---|---|
| 1 | Upstream/Downstream_Unknown |
| 2 | Upstream/Downstream_Upstream |
| 3 | PType_Single |
| 4 | PShape_Round |
| 5 | PShape_Sharp |
| 6 | PShape_Square |
| 7 | Sediment_Transport_Live-bed |
| 8 | Sediment_Transport_Unknown |
| 9 | Bed_Material_Unknown |
| 10 | Debris_Effects_Moderate |
| 11 | Debris_Effects_Substantial |
| 12 | Debris_Effects_Unknown |

**Artificial Neural Network**

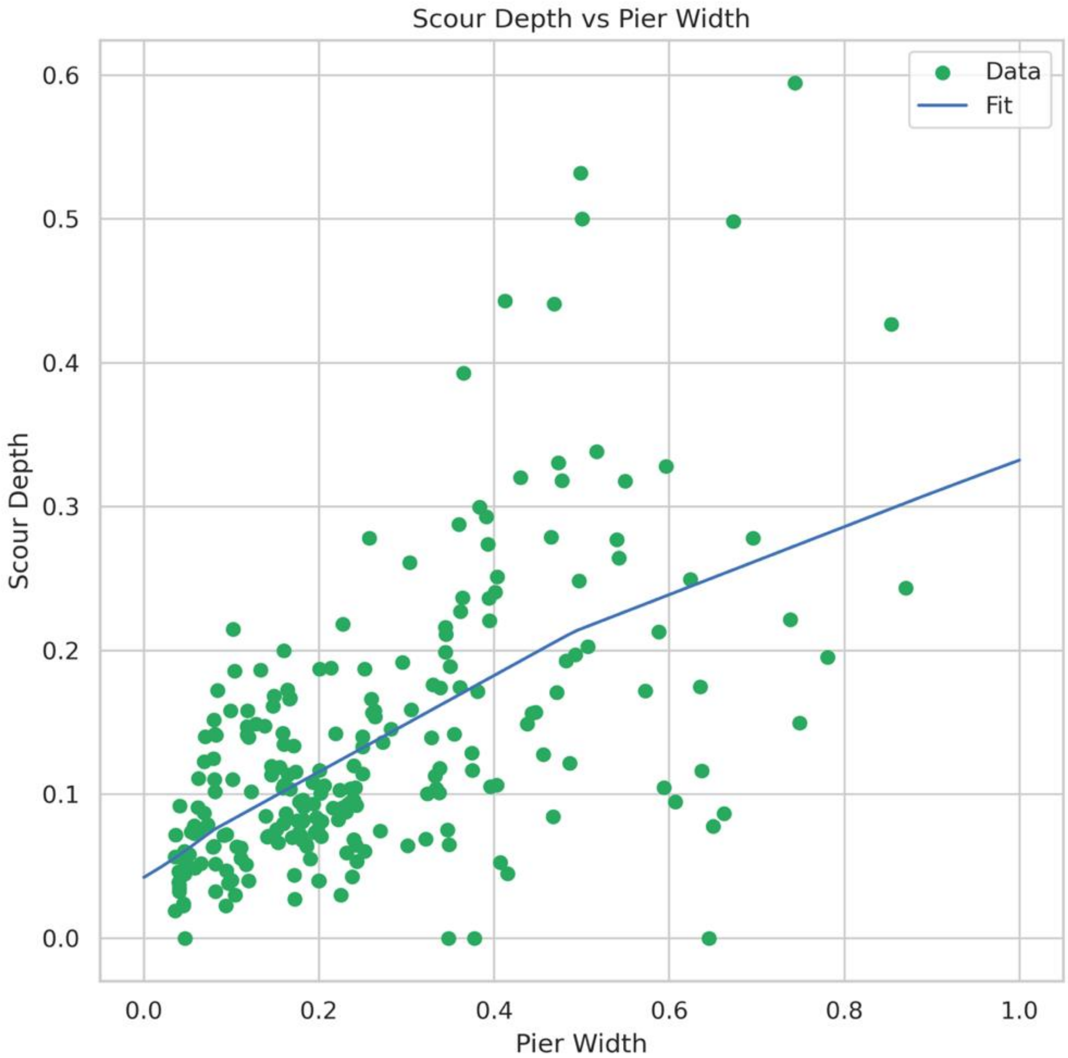
- **Single Feature Model - Width (Test Loss: 0.005776) (Graph 8):** The learning curve for the Artificial Neural Network (ANN) Single Feature Model exhibits a steady decrease in test loss over the training epochs, reaching a minimal value of 0.005776. This indicates that the model effectively captures the underlying patterns in the data.

- **Datapoints and Best Fit Line (Graph 9):** The scatter plot showcases the relationship between predicted and actual values for the single-feature ANN model. The alignment of data points along the best-fit line demonstrates the model's ability to make accurate predictions, particularly in capturing the nuances of the chosen single feature.

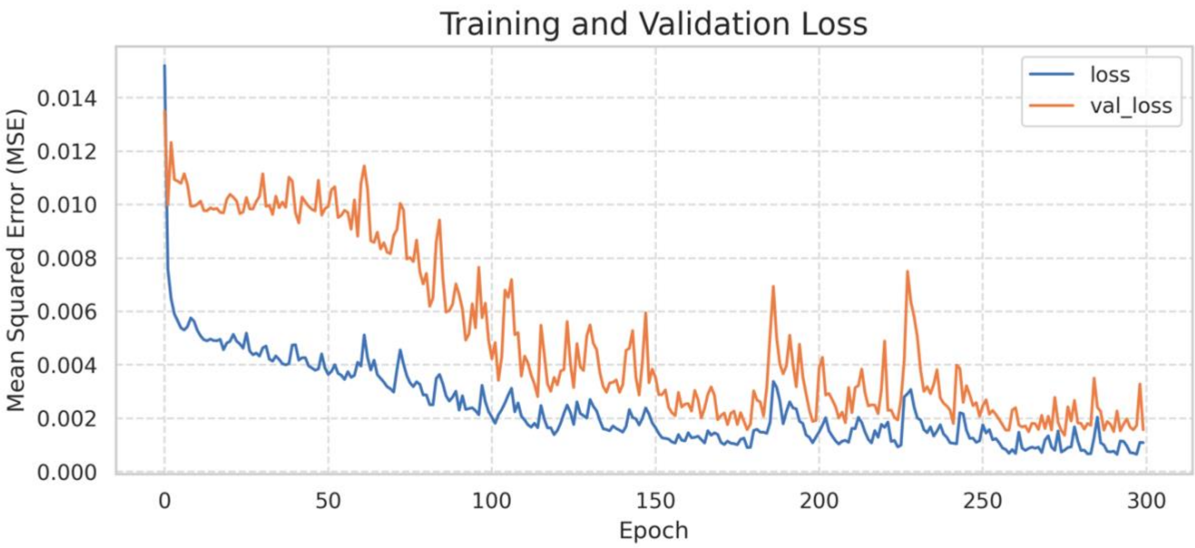
- **Multiple Feature Model (Test Loss: 0.001754) (Graph 10):** The learning curve for the ANN Multi-Feature Model further emphasizes the model's performance, achieving a lower test loss of 0.001754. This underscores the advantage of incorporating multiple features in enhancing predictive capabilities.

- **Actual and Predicted Datapoints (Graph 11):** The combined scatter plot illustrates the accuracy of the multi-feature ANN model in predicting scour depths. The proximity of actual and predicted values validates the model's effectiveness in handling the complexity introduced by multiple input features.

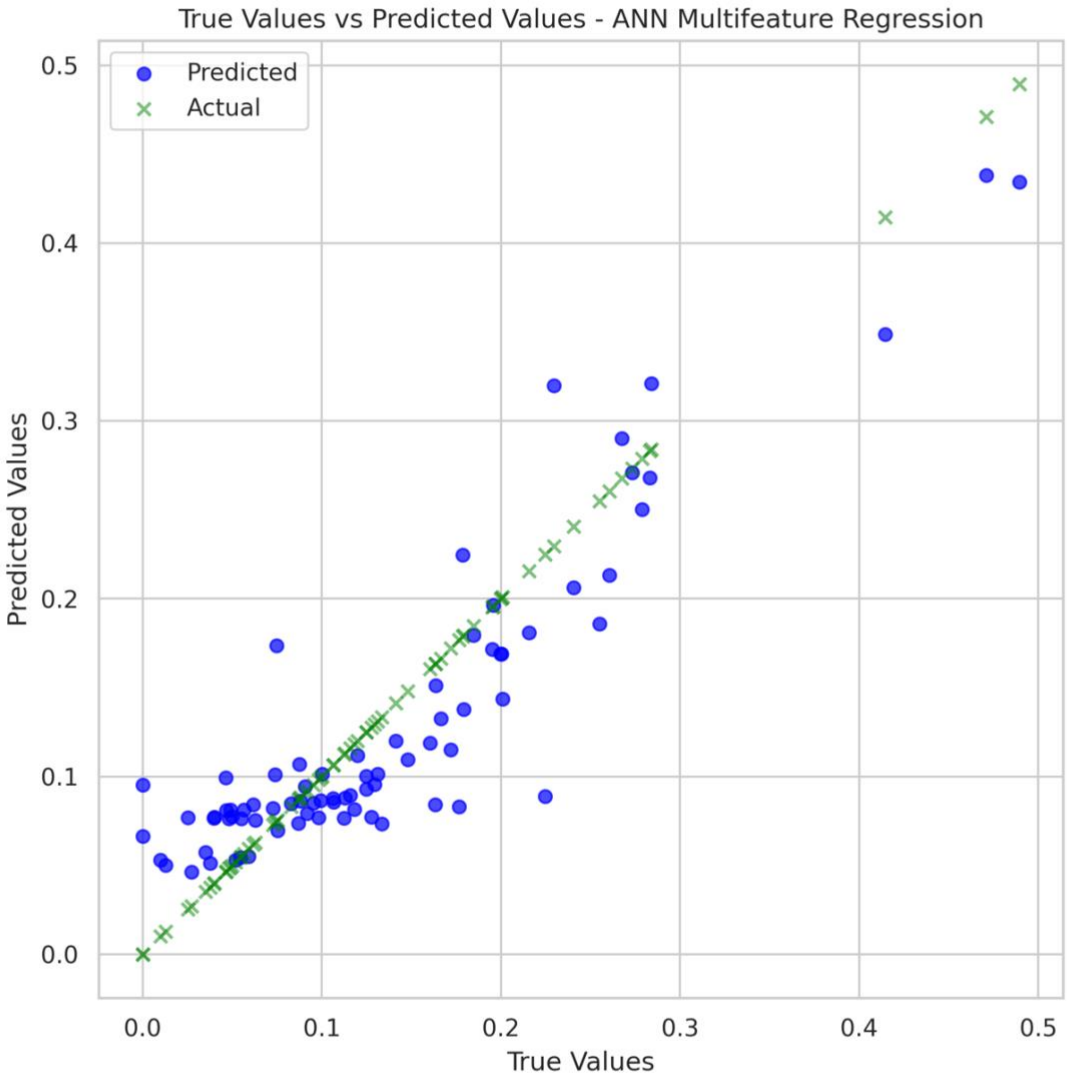

***Graph 8:*** *ANN Single Feature Model Learning Curve (Test Loss: 0.005776)*




***Graph 9:*** *Datapoints and best fit line (Single Feature - ANN)*




***Graph 10:*** *ANN Multi Feature Model Learning Curve (Test Loss:* 0.001754*)*




***Graph 11:*** *Actual(combined) and predicted datapoints (Multi Feature - ANN)*

**Support Vector Regression**

- **Datapoints and Best Fit Line (Graph 12):** The SVR Single Feature Model, employing a linear kernel, exhibits a scatter plot with a best-fit line. This visualization provides insights into the model's performance in capturing the linear relationship between the single feature and scour depth.

- **Actual and Predicted Datapoints (Graph 13):** The scatter plot for the SVR Multi-Feature Model showcases the model's ability to handle the complexity of multiple features. The alignment of actual and predicted data points indicates the model's proficiency in capturing the underlying patterns within the dataset.

## Single Regression - Width

[82]
```python
'''Create and train the SVM regression model

You can choose different kernels like 'linear',
'rbf', 'precomputed', 'sigmoid', 'poly'.'''

svmRegWidth = SVR(kernel='linear')
svmRegWidth.fit(XtrainWidth, ytrainWidth)
```

```
SVR
SVR(kernel='linear')
```

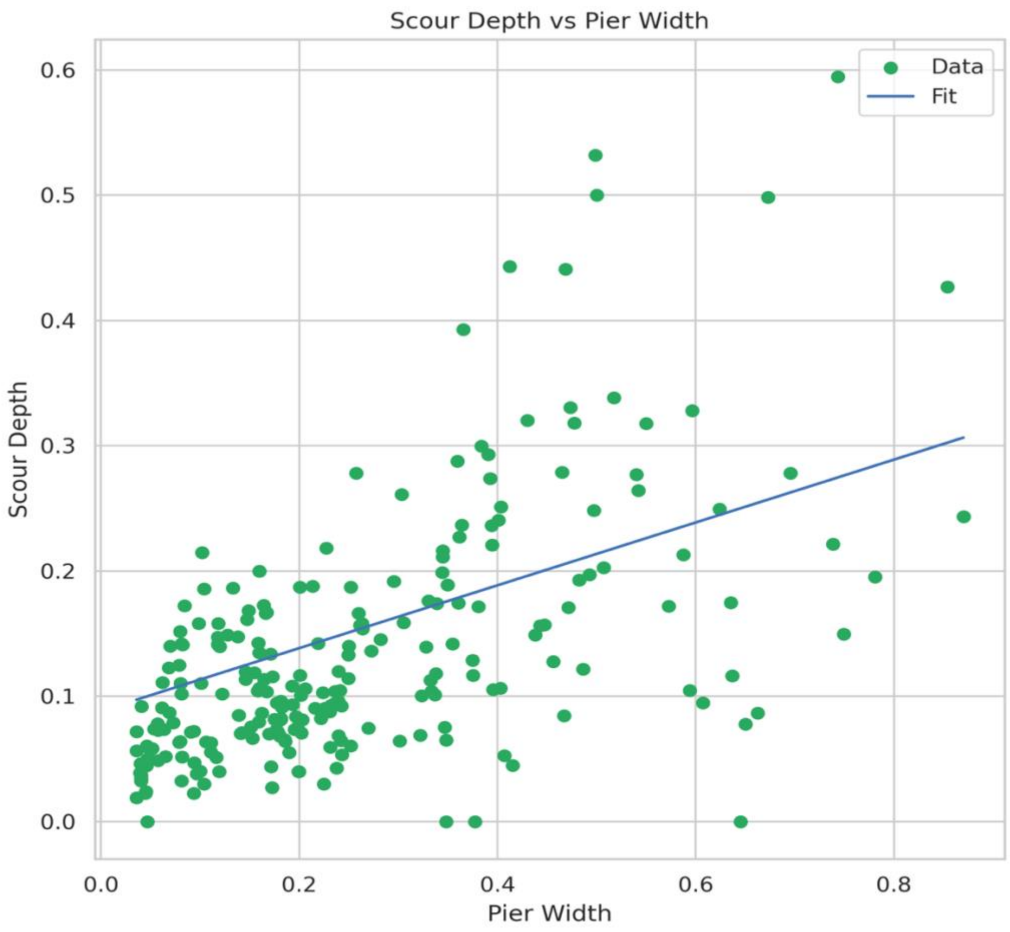
[83]
```python
ypredWidth = svmRegWidth.predict(XtestWidth)

#Save the model
joblib.dump(svmRegWidth, './svmRegWidth.pkl')

# Evaluate the model
score = svmRegWidth.score(XtestWidth, ytestWidth)
print("R-squared score on the test set:", score)
mse = mean_squared_error(ytestWidth, ypredWidth)
print(f'Mean Squared Error: {mse}')
```

```
R-squared score on the test set: 0.337061265351671
Mean Squared Error: 0.006393804923533176
```

***Image 1:*** *Single feature (pier width) regression model using SVR*




***Graph 12:*** *Datapoints and best fit line (Single Feature - SVR).*

## Multiple Regression

```python
[85]
'''
Create and train the SVM regression model
You can choose different kernels like 'linear',
'rbf', 'precomputed', 'sigmoid', 'poly'.
'''
svmRegAll = SVR(kernel='linear')
svmRegAll.fit(XtrainAll, ytrainAll)
```

```
SVR
SVR(kernel='linear')
```

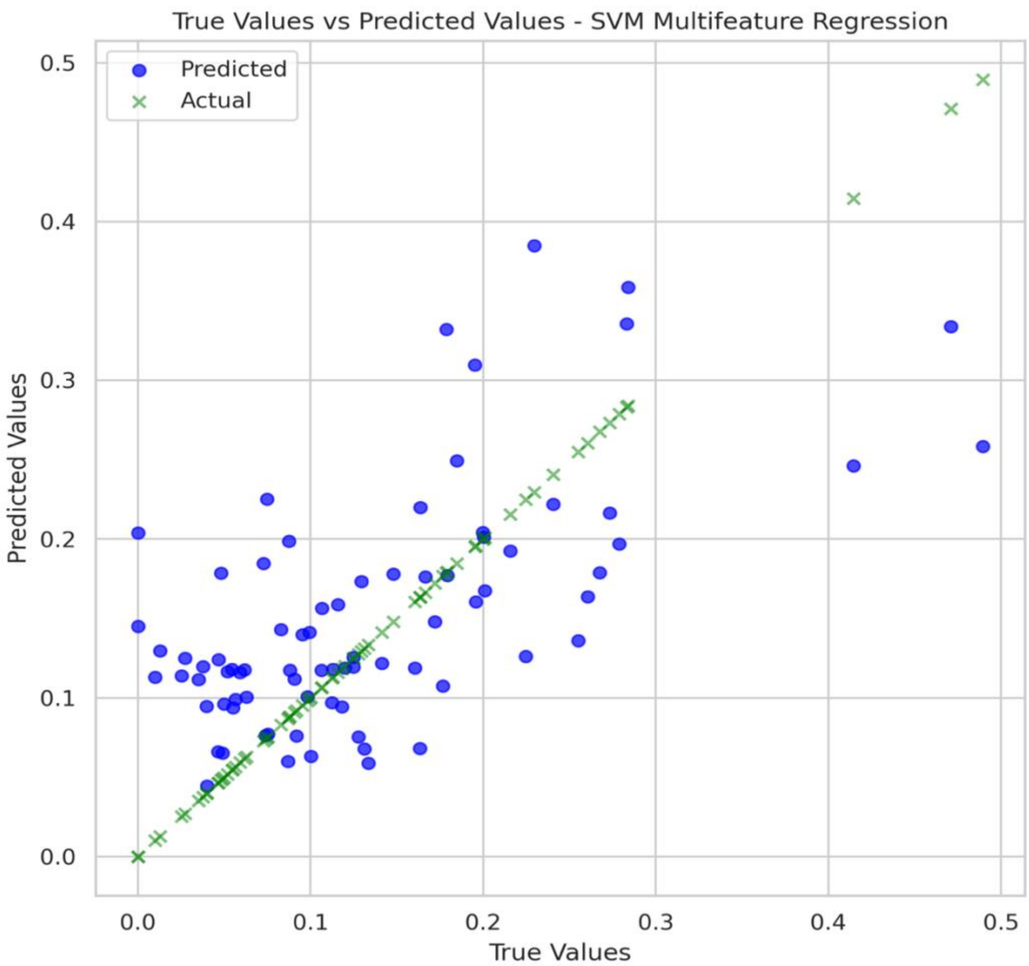
```python
ypredAll = svmRegAll.predict(XtestAll)

#Save the model
joblib.dump(svmRegAll, './svmRegAll.pkl')

# Evaluate the model
score = svmRegAll.score(XtestAll, ytestAll)
print("R-squared score on the test set:", score)
mse = mean_squared_error(ytestAll, ypredAll)
print(f'Mean Squared Error: {mse}')
```

```
R-squared score on the test set: 0.3543737882610378
Mean Squared Error: 0.006226831886008961
```

***Image 2:*** *Multiple feature regression model using SVR*




***Graph 13:*** *Actual(combined) and predicted datapoints (Multi Feature - SVR)*

**Overall Observations:**

- The presented visualizations affirm the efficacy of both ANN and SVR models in predicting scour depths around hydraulic structures.
- The **multi-feature models consistently outperform their single-feature counterparts**, highlighting the importance of considering a holistic set of features for accurate predictions.
- The model with the best performance is the **"ANN Multiple Feature Model ", which has the lowest MSE, 0.001754.**
- The precise alignment of data points along the best-fit lines in the scatter plots underscores the models' reliability and potential for practical applications.

## 7. Conclusion

In conclusion, the research endeavours focused on developing and evaluating predictive models for scour depth around hydraulic structures have yielded insightful outcomes. Through the utilization of Artificial Neural Networks (ANN) and Support Vector Regression (SVR) techniques, the following key findings and conclusions can be drawn:

- **Model Performance:**
  - The ANN models, both single-feature and multi-feature, demonstrate robust performance, achieving low test losses of 0.005776 and 0.001754, respectively. This affirms the efficacy of artificial neural networks in capturing intricate relationships within the dataset.
  - The SVR models, particularly with a linear kernel, showcase notable predictive capabilities. The R-squared scores of 0.337 (single-feature) and 0.354 (multi-feature) indicate the models' ability to explain variability in scour depth based on the chosen features.

- **Feature Importance:** Multi-feature models consistently outperform their single-feature counterparts, emphasizing the importance of considering diverse input features. Incorporating information from various aspects, such as hydraulic structures, flow patterns, and sediment properties, enhances the models' predictive accuracy.

- **Visualization Insights:** The learning curves and scatter plots presented provide valuable insights into the training and predictive capabilities of the models. The alignment of actual and predicted data points, along with the clear trends observed in the best-fit lines, underscores the reliability of the developed models.

- **Practical Implications:** The developed predictive models have the potential for practical applications in assessing scour depths around hydraulic structures. The accuracy demonstrated by the models is crucial for engineering decisions related to structure design, maintenance, and risk mitigation.

- **Future Directions:** Further refinement and exploration of advanced modelling techniques, ensemble methods, and feature engineering could enhance the predictive performance of the models.

In summary, this project contributes valuable tools for predicting scour depths, which is crucial for the maintenance and safety of hydraulic structures. The combination of ANN and SVR models, informed by a comprehensive dataset, presents a promising avenue for addressing the complexities associated with scour depth prediction in real-world scenarios.

## 8. Monthly Work Plan

***Table. 2: Monthly Plan Table***

| S. N0 | Start Date | Finish Date | Task | Status |
|---|---|---|---|---|
| 1 | September 16 | September 30 | Literature Review | Completed |
| 2 | October 11 | October 25 | Data Collection | Completed |
| 3 | October 26 | October 30 | Data Pre-processing | Completed |
| 4 | October 31 | November 5 | Feature Selection/Engineering | Completed |
| 5 | November 6 | November 15 | Algorithm Selection (ANN, SVM, etc.) | Completed |
| 6 | November 16 | December 12 | Model Development and Optimization | Completed |

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