IJARSCT
ISSN: 2581-9429
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Volume 5, Issue 4, April 2025
Impact Factor: 7.67

Result Analysis and SGPA Prediction using SVR and LSR: A Comparative Analysis

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Abstract: *Predictive models in education leverage statistical and machine learning techniques to analyze a wide range of student data, including demographics, learning behaviors, test scores, and engagement metrics. The models aim to predict various academic outcomes such as student performance, retention rates, and dropout risks. These insights can help educators tailor learning experiences to individual students, implementing personalized interventions and support strategies where needed. Predictive analytics also enhances the effectiveness of educational institutions by identifying at-risk students early and optimizing resource allocation. The focus of this research is specifically on academic performance prediction, with an emphasis on grade forecasting. By examining existing approach in this area, the research implements the methodologies and tools used to predict student grades, uncovering patterns and trends that could lead to improved educational practices. This research paper details implementation of the above ideology on live data using Support Vector and Least Square Regression. The research also details on student segregation using KNN approach which helps catering to different students with different intellectual capabilities. The ultimate goal of this research is to bridge the gap between students' current performance and their academic potential, fostering better outcomes for all learners.*

Keywords: RAPS (Result Analysis & Prediction System), Predictive Modeling, Support Vector Regression (SVR), Least Square Regression (LSR)

I. INTRODUCTION

Prediction is a powerful data analysis task used to determine the future behavior of a user or a system. The task of prediction has aided the decision makers to take the right decision at the right time.

A. Problem Statement

Accurately analyzing past results and predicting future outcomes remains a significant challenge due to the complexity of data, its inconsistency, and the need for selecting appropriate predictive models. Developing a robust result analysis and prediction system is crucial to handle large dataset thereby enabling informed decision-making and optimal outcomes in various sectors.

B. Background of the Study

Predicting student performance is crucial in education, involving analysis of historical data to forecast outcomes. This process uses data analytics, statistical models, and machine learning to identify patterns and trends. Systems can predict student performance based on previous grades and attendance. Key steps include data collection, pre-processing, and feature selection to enhance prediction accuracy. Common methods are regression analysis, classification models, and time series analysis. Prediction accuracy relies on data quality and model suitability. These systems help organizations optimize strategies, improve performance, and allocate resources effectively, making result analysis and prediction vital for informed decision-making.

C. Objectives of the Research

The research objective of this study is:

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- To explore and implement the methodology and approaches adopted in building a predictive model.
- To analyze the algorithms and techniques used in predicting the performance of students.
- To identify the features used for building the prediction models.
- To evaluate the model using performance metrics.

D. Scope and Limitations

A result analysis and prediction system uses historical data to forecast future outcomes, aiding decision-making in sectors like education, healthcare, finance, and marketing. Its goal is to enhance accuracy, efficiency, and resource allocation by identifying trends. However, the system faces challenges, including dependence on high-quality, complete data, which can be hard to obtain. Model accuracy may suffer from biases, data inconsistencies, or unpredictable external factors. While predictions offer valuable insights, they may not always be reliable due to the complexity of real-world variables.

II. LITERATURE REVIEW

A. Overview of Previous Work

The prediction of student performance is a key research area utilizing various machine learning algorithms for academic outcomes like GPA and test scores.

- Linear Regression (Pham Xuan Lam et al., 2024; Sai Battula) [12] predicts continuous outcomes like GPA with up to 89% accuracy.
- Decision Trees (Esmael Ahmed, 2024) [11] classify performance effectively, achieving 93.4% accuracy.
- Support Vector Machines (Shah Hussain, 2023) [2] handle complex data, reaching 96% accuracy.
- Random Forests (Pham Xuan Lam, 2024) [1] manage large datasets with 91.71% accuracy.
- Naïve Bayes (Areej Alhothali, 2022) [8] predicts online course success with 85% accuracy.
- Deep Learning Models (Stephen Opoku Oppong, 2023) [9] model complex patterns, achieving 82.7% accuracy.

Each method has distinct strengths based on data type and prediction complexity.

B. Key Approaches to Result Analysis and Prediction

The key approaches used in result analysis and prediction can be broadly categorized as:

- Regression Models (Linear Regression): These models are primarily used for continuous outcome predictions such as GPA or test scores. They establish a linear relationship between input features and the target variable.
- Classification Models (Decision Tree, Naïve Bayes, Random Forest): These models classify students into categories like "high performer" or "low performer".
- Support Vector Machines (SVM): SVMs are used for classification and regression, particularly when data is non-linear and complex. The technique maximizes the margin between classes and is effective in highdimensional spaces.
- Deep Learning Models: These models are capable of capturing highly complex patterns, especially when dealing with large datasets with numerous features.

C. Gaps in Existing Research

While numerous models have been proposed for student performance prediction, there are still notable gaps in the existing research:

- Data Quality and Availability: Datasets can be incomplete, noisy, or lack diversity, which limits the generalizability of prediction models.
- Model Interpretability: Complex models like Deep Learning and SVMs often lack interpretability, making it challenging to understand the factors that lead to predictions.

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- Feature Selection and Engineering: Many studies do not fully explore the optimal features that contribute to better predictive accuracy.

III. METHODOLOGY

A. Model Architecture

The process begins with data collection, followed by data pre-processing to clean and structure the dataset. The model training phase utilizes this processed data to build a predictive model, which is then evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Accuracy, R-Squared Error, and Explained Variance Score. The trained model is integrated into the system via an API, allowing it to predict SGPA based on input data. This structured approach ensures efficient and accurate academic performance prediction

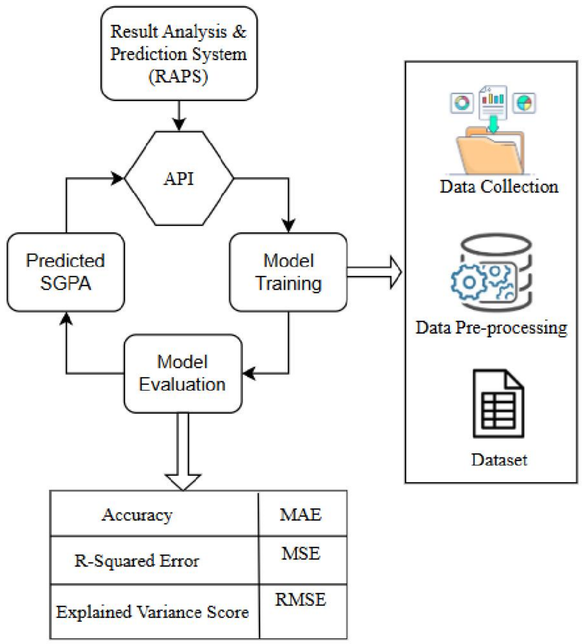

Fig. 1. Model Architecture Result Analysis & Prediction System

B. Data Flow Diagram

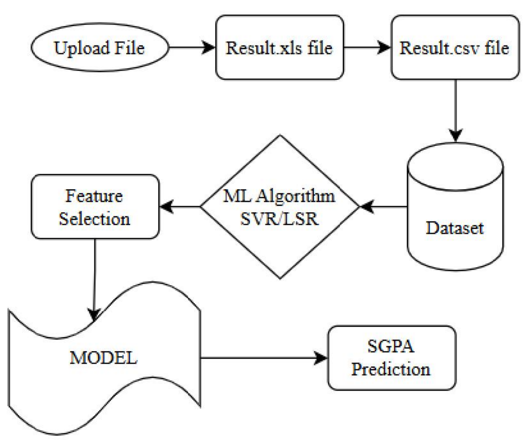

Fig. 2. Data Flow Diagram

DOI: 10.48175/IJARSCT-25176

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International Journal of Advanced Research in Science, Communication and Technology
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IV. PRE-PROCESSING

A. Data Collection

The data for this study was collected from the faculty of the selected academic institution. The dataset consisted of two main components: internal marks and external grades. Internal marks referred to the marks obtained by students in coursework, assignments, and exams throughout the semester, while external grades represented the final grades (classified as O, A, B, C, D, E, F) received by students at the end of the semester. This data was gathered from the academic records of students who were part of a specific batch.

B. Data Preparation and Cleaning

The following steps were undertaken to pre-process and clean the data:

- Retrieving Student Records: The first step involved retrieving the list of students belonging to the selected batch which included both internal marks and external grades. label*=0.
- Fetching SGPA Records from Previous Semesters: For each student, the SGPA records from previous semesters were fetched. These records provided a istorical view of the student's performance that were essential for predictive analysis.
- Handling Missing SGPA Values: Missing SGPA were replaced with the mean SGPA of the semesters for that student. This helped to avoid the exclusion of incomplete records while maintaining a consistent representation of the student's academic trajectory.
- Identifying Valid Semesters: Valid semesters were identified by checking the availability of non-null SGPA values. Only semesters with valid SGPA values were considered when preparing the dataset for training the model. This step ensured that the model was trained using accurate and reliable data.
- Feature and Label Preparation: In the dataset, the semesters served as the features (independent variable, X), while the corresponding SGPA values were taken as the labels (dependent variable, Y).

C. Attribute and Feature

The attributes and features used in the prediction process are critical for the accuracy and reliability of the prediction. Let's break down the key features involved:

1) Historical SGPA Data

The primary feature for predicting SGPA is the student's historical SGPA data across different semesters. The historical data helps the model to understand the trends in the student's academic performance and predict the SGPA for the upcoming semester. The attributes are:

- rollno: The unique identifier for each student, linking the SGPA data to a student.
- sem: The semester number in which the SGPA was obtained.
- sgpa: The SGPA achieved by the student in that semester.

2) Semester Numbers (x)

The semester numbers are used as the independent variable (input) for the regression model. These semester values act as the feature input to the model. Attributes:

• sem: Each semester's numeric identifier (e.g., 1 for Semester 1, 2 for Semester 2).

V. RESULT ANALYSIS

This section focuses on high level overview of the various means of results analysis provided in our system

A. Report Generation

The Reports are dynamically generated to provide insights into student performance across subject s and semesters.

- Overall Semester Performance: Number of students who appeared, passed and overall pass percentage.
- Failure Analysis: Categorizes students based on the number of subjects they failed in.

- Subject-wise Performance: List each subject along with the faculty name, total students who appeared, number of student passed, passed percentage.

B. Batch Comparison
This analysis compares the results of batch with other batch that helps to evaluate performance, assess the curriculum and analyze faculty effectiveness. The key features are:
- Batch &Semester selection: Users can compare specific batches and semesters for better insights.
- Automated Data Processing: Eliminates manual efforts and improves accuracy.
- SGPA Analysis: Displays average performance metrics.
- Pass/Fail Count: Provides insights into success rate of students.
- Visual Representation: Includes Charts for better comparison.

C. Performance Analysis and Feedback Generation
The student analysis system uses GEMINI to evaluate the strengths and weaknesses based on the subject tags and the students' performance in it.
- SGPA Variation: This analyses the SGPA of the student across various semesters.
- Strength Identification: Strengths are determined by analyzing the grades, and performance across the subject. If the grade is 'O' or 'A'.
- Intermediate Performance: If the grade is 'B' or 'C'.
- Weakness Identification: Subjects where the students consistently score low are flagged as weak areas. If the grade is 'D' or below.
- Feedback Generation with Gemini: Feedback tailored to the student's performance is provided that encourages students to improve their weaknesses while reinforcing their strengths.

D. Student Segregation
The student segregation mechanism is designed to classify students into three categories: Advanced, Intermediate and weak learners based on their SGPA. The classification is done using the K-Nearest Neighbours (KNN) algorithm. Each students SGPA is used as a feature for classification.

Advanced Learner: SGPA ≥ 8

Intermediate Learner: $6 \leq$ SGPA < 8

Weak Learner: SGPA < 6

1) KNN Pseudocode for Student Segregation
```
BEGIN
  INPUT batch_year
  FETCH student data (roll number, name, average SGPA) WHERE join_year = batch_year
  INITIALIZE samples = []
  INITIALIZE labels = []
  FOR each student in fetched data:
    avg_sgpa = student's average SGPA
    // Assign category based on SGPA
    IF avg_sgpa >= 8 THEN
      category = "Advanced"
    ELSE IF avg_sgpa >= 6 THEN
      category = "Intermediate"
    ELSE
      category = "Weak"
```

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```
        ENDIF
        ADD avg_sgpa to samples
        ADD category to labels
    ENDFOR
    // Train K-Nearest Neighbors (KNN) Classifier
    INITIALIZE classifier as KNN
    TRAIN classifier using samples and labels
    // Classify students
    INITIALIZE advanced_learners = []
    INITIALIZE intermediate_learners = []
    INITIALIZE weak_learners = []
    FOR each student in fetched data:
        avg_sgpa = student's average SGPA
        prediction = classifier.predict([avg_sgpa])
        IF prediction == "Advanced" THEN
            ADD student to advanced_learners
        ELSE IF prediction == "Intermediate" THEN
            ADD student to intermediate_learners
        ELSE
            ADD student to weak_learners
        ENDIF
    ENDFOR
    DISPLAY categorized students in separate tables
    PROVIDE download option for each category as an Excel sheet
END
```

VI. PREDICTION MODEL

A. Prediction Algorithm

The prediction focuses on predicting the SGPA (Semester Grade Point Average) for the next semester based on the historical data of SGPA values from previous semesters. We have implemented two algorithms, Support Vector Regression (SVR) and Least Square Regression (LSR). These are particularly useful for predicting continuous numerical values like SGPA.

Least Squares Regression (LSR) is a method used to find the best-fitting line or curve by minimizing the sum of squared differences between observed values and the predicted values. It models relationships between dependent and independent variables, optimizing predictions and minimizing errors.

SVR (Support Vector Regression) works by finding a hyperplane that best fits the data points while keeping the error within a predefined threshold. For this task, the Radial Basis Function (RBF) kernel is used, capturing non-linear relationships between the semesters (independent variable) and SGPA values (dependent variable).

1) Extract Valid SGPA Data

The first step involves collecting the historical SGPA data for each student. The goal is to prepare the data in a format suitable for machine learning.

Fetching Historical Data: The algorithm queries a database to retrieve all historical SGPA data for each student.

2) Pre-process Data

After extracting the SGPA data, the next step is data preprocessing, where the algorithm cleans and prepares the data for the model.

• Filling Missing Values:

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Calculate the Mean SGPA: The algorithm calculates the mean SGPA from the available data.
Replace Missing SGPA with Mean: If a student has missing SGPA values for a semester (e.g., they have not completed that semester yet), the missing value can be replaced with the mean SGPA calculated from the student's other valid semesters.
Reasoning: This step ensures the prediction model doesn't face any gaps in the data while still working with a realistic estimate of the student's performance.
Filtering Invalid Data: After handling missing values, it's essential to ensure that only valid SGPA data is used. If there are any remaining null values (perhaps after replacing them with the mean), they are removed from the dataset. This ensures that only meaningful data is passed to the machine learning model.

3) Train the Model

The next step is to train the model where the goal is to predict a continuous output (SGPA for the next semester).
• Choose the Features and Target Variable:
Features (x): The independent variable is the semester number.
Target (y): The dependent variable is the SGPA value.
Training the Model: The model is trained using the feature set (semester numbers) and the target set (SGPA values). The model learns a mapping between the semesters and SGPA values.

4) Make Predictions

After the model has been trained, the next step is to make predictions for future data (SGPA for the next semester).
Predict the SGPA : Once the model is trained, it can predict the SGPA for the next semester. The algorithm takes the next semester number (i.e., one semester after the most recent semester) as input and passes it through the trained model.
Capping the Predicted SGPA: Valid SGPA Range: Since SGPA typically falls within a range (e.g., 1 to 10), the predicted SGPA is capped within this range to avoid unrealistic values.

B. SVR Pseudocode for Prediction

```
START
  # Step 1: Extract Valid SGPA Data for each student
  FOR each student in database DO
    # Fetch the student's historical SGPA data
    sgpa_data = fetch_SGPA_for_student(student)
    # Initialize a list to store valid SGPA data
    valid_sgpas = []
    valid_semesters = []
    # Loop through the SGPA data
    FOR each semester, sgpa in sgpa_data DO
      IF sgpa is valid THEN
        # Add valid SGPA and its corresponding semester to the lists
        Append semester to valid_semesters
        Append sgpa to valid_sgpas
      ELSE
        # Replace missing SGPA with the mean SGPA if necessary
        predicted_sgpa = calculate_mean(valid_sgpas)
        Append predicted_sgpa to valid_sgpas
        Append semester to valid_semesters
      END IF
    END FOR
```

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```
    # Step 2: Preprocess the data (handle missing SGPA, replace with mean)
    valid_sgpas, valid_semesters = preprocess_data(valid_sgpas, valid_semesters)
    # Step 3: Train the Support Vector Regression (SVR) Model
    IF number of valid semesters >= 2 THEN
      # Train the SVR model on valid data (semesters and SGPA values)
      model = train_SVR_model(valid_semesters, valid_sgpas)
    ELSE
      # Skip prediction if there are not enough data points
      CONTINUE
    END IF
    # Step 4: Predict the SGPA for the next semester (next semester after the most recent)
    next_semester = max(valid_semesters) + 1
    # Predict the SGPA for the next semester using the trained model
    predicted_sgpa = model.predict([next_semester])
    # Step 5: Cap the predicted SGPA between 1 and 10 to ensure it's within a valid range
    IF predicted_sgpa < 1 THEN
      predicted_sgpa = 1
    ELSE IF predicted_sgpa > 10 THEN
      predicted_sgpa = 10
    END IF
    # Step 6: Display or store the predicted SGPA for this student
    Display or store student, valid_sgpas, predicted_sgpa
  END FOR
END
```

C. Least Square Regression Pseudocode for Prediction

```
START
  # Step 1: Extract Valid SGPA Data for each student
  FOR each student in database DO
    # Fetch the student's historical SGPA data for each semester
    sgpa_data = fetch_SGPA_for_student
    # Initialize a list to store valid SGPA data and semesters
    valid_sgpas = []
    valid_semesters = []
    # Loop through the SGPA data for each semester
    FOR each semester, sgpa in sgpa_data DO
      IF sgpa is valid THEN
        # Add valid SGPA and its corresponding semester to the lists
        Append semester to valid_semesters
        Append sgpa to valid_sgpas
      ELSE
        # Replace missing SGPA with the mean SGPA if necessary
        predicted_sgpa = calculate_mean(valid_sgpas)
        Append predicted_sgpa to valid_sgpas
        Append semester to valid_semesters
      END IF
    END FOR
```

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```
        # Step 2: Preprocess the data (handle missing SGPA, replace with mean)
        valid_sgpas, valid_semesters = preprocess_data(valid_sgpas, valid_semesters)

        # Step 3: Train the Least Squares Regression Model
        IF number of valid semesters >= 2 THEN
            # Train the Least Squares Regression model on valid data (semesters and SGPA values)
            model = train_LeastSquares_model(valid_semesters, valid_sgpas)
        ELSE
            # Skip prediction if there are not enough data points
            CONTINUE
        END IF

        # Step 4: Predict the SGPA for the next semester (next semester after the most recent)
        next_semester = max(valid_semesters) + 1
        # Predict the SGPA for the next semester using the trained model
        predicted_sgpa = model.predict([next_semester])

        # Step 5: Cap the predicted SGPA between 1 and 10 to ensure it's within a valid range
        IF predicted_sgpa < 1 THEN
            predicted_sgpa = 1
        ELSE IF predicted_sgpa > 10 THEN
            predicted_sgpa = 10
        END IF
        # Step 6: Display or store the predicted SGPA for this student
        Display or store student, valid_sgpas, predicted_sgpa
    END FOR
END
```

VII. EXPERIMENTAL RESULTS

The Data being employed for the research and hence being used for Result Analysis and Prediction by the built system is live Batch-wise data of the students of Stanley College.

A. Model Evaluation 5th Semester Prediction

Table I Model Evaluation of 5th Semester Prediction

S.No	Error Metric	Support Vector Regression(SVR)	Least Square Regression (LSR)	Interpretation
1.	Mean Absolute Error (MAE)	1.05	0.75	LSR performs better with lower absolute error.
2.	Mean Square Error (MSE)	5,50	4.95	LSR has fewer extreme errors compared to SVR.
3.	Root Mean Square Error (RMSE)	2.34	2.23	LSR has better error minimization.
4.	R-Squared Score	0.52	0.65	LSR explains more variance, making it a better model.
5.	Explained Variance Score	0.50	0.63	LSR captures more variability in student performance.

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B. Model Evaluation 6th Semester Prediction

Table II Model Evaluation of 6th Semester Prediction

S. No	Error Metric	Support Vector Regression(SVR)	Least Square Regression(LSR)	Interpretation
1.	Mean Absolute Error (MAE)	0.71597	0.70164	Both have similar MAE.
2.	Mean Square Error (MSE)	1.3238	1.3638	SVR has a lower MSE, indicating fewer large squared errors in its predictions.
3.	Root Mean Square Error (RMSE)	1.15	1.167	SVR has a smaller RMSE, meaning it has fewer large errors than LSR.
4.	R-Squared Score	0.57758	0.5622	SVR fits the data better with a higher R-squared, explaining more variance in the actual values.
5.	Explained Variance Score	0.512	0.54	LSR explains a higher proportion of the variance in the actual SGPA.

C. Model Evaluation 7th Semester Prediction

Table III Model Evaluation of 7th Semester Prediction

S.No	Error Metric	Support Vector Regression(SVR)	Least Square Regression(LSR)	Interpretation
1.	Mean Absolute Error (MAE)	0.67	0.62	LSR has a lower MAE, meaning the average error for LSR is smaller than SVR, suggesting that LSR's predictions are closer to the actual values on average.
2.	Mean Square Error (MSE)	0.75	0.56	LSR has lower MSE which suggest that on average, the squared differences between predicted and actual SGPA are lower for LSR compared to SVR.
3.	Root Mean Square Error (RMSE)	0.86	0.75	LSR is slightly better than SVR in terms of average magnitude of error.
4.	R-Squared Score	0.66	0.73	LSR explains 73% of the variance in the actual values, whereas SVR explains only 66%. LSR fits the data better than SVR.
5.	Explained Variance Score	0.62	0.69	LSR explains 69% of the variance, while SVR explains only 62%. This aligns with the R-squared value, confirming that LSR explains more of the variance.

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VII. COMPARATIVE ANALYSIS

Key Findings: A Comparative Analysis of 5th Semester Predictions

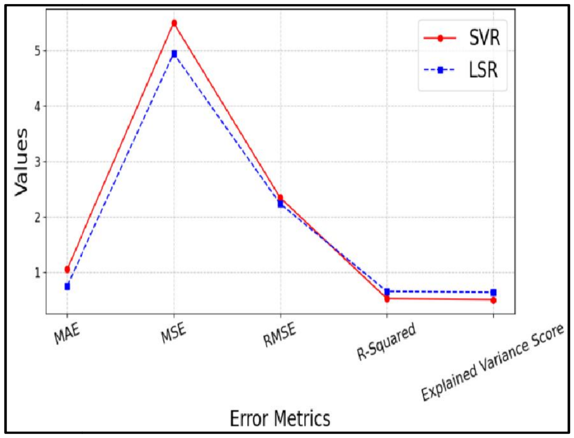

Fig. 3. SVR vs LSR: 5th Semester Predictions

B. Key Findings: A Comparative Analysis of 6th Semester Predictions

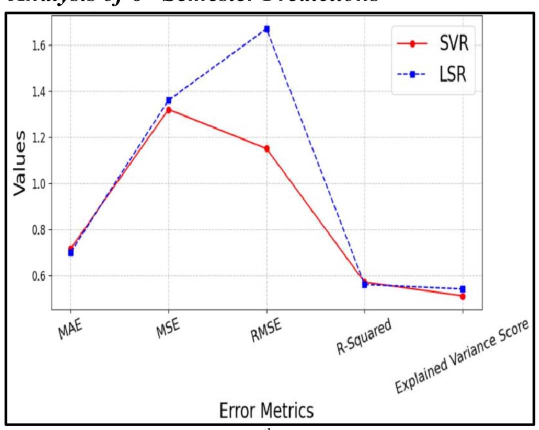

Fig. 4. SVR vs LSR 6th Semester Predictions

C. Key Findings: A Comparative Analysis of 7th Semester Predictions

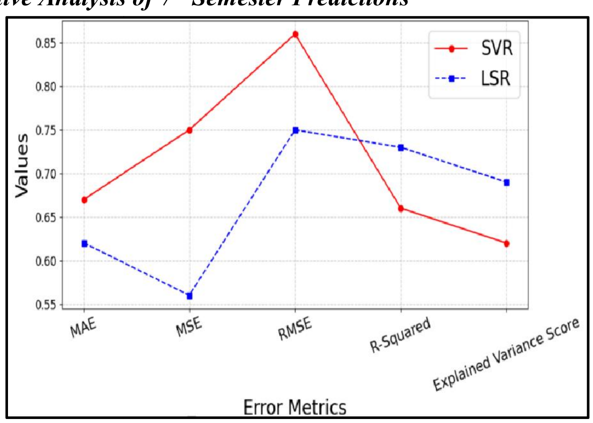

Fig. 5. SVR vs LSR 7th Semester Predictions

VIII. CONCLUSION

The comparative analysis of Support Vector Regression (SVR) and Least Square Regression (LSR) for SGPA prediction reveals significant insights into the performance of both models. The results indicate that LSR generally outperforms SVR across all evaluation metrics, suggesting its higher accuracy and better predictive capability for SGPA prediction.LSR achieved an accuracy of 83.58%, surpassing SVR's 77.61%, indicating that LSR is more reliable in predicting SGPA values. Additionally, LSR demonstrated lower Mean Absolute Error (MAE) and Mean Squared Error (MSE), which means that LSR's predictions are closer to the actual values on average. This is further supported by the lower Root Mean Square Error (RMSE) in LSR, confirming that LSR's predictions exhibit smaller average magnitudes of error. The R-Squared and Explained Variance Scores also favor LSR, with LSR explaining 73% of the variance in the data compared to 66% for SVR. LSR's superior ability to explain the variance further highlights its better fit to the data. Additionally, the Explained Variance Score for LSR (47%) is significantly higher than SVR's (2%), reinforcing that LSR captures more of the data's underlying patterns.

In conclusion, LSR proves to be the more effective model for SGPA prediction in this study, offering higher accuracy and more reliable results across multiple metrics. Future research can focus on exploring other machine learning models and feature engineering techniques to further improve the prediction accuracy and address potential limitations observed in the current models.

IX. ACKNOWLEDGMENT

The heading of the Acknowledgment section and the References section must not be numbered.Causal Productions wishes to acknowledge Michael Shell and other contributors for developing and maintaining the IEEE LaTeX style files which have been used in the preparation of this template.

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