e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issu:04/April-2025 Impact Factor- 8.187 www.irjmets.com

DESIGNING AN INTELLIGENCE QUOTIENT (IQ) BASED STUDENT ASSESSMENT MODEL UTILIZING MACHINE LEARNING

P. Kamakshi Thai[*1], Mohammed Aleem Pasha[*2], Mohammed Afrose Ahmed[*3], ManuKonda Arun Sahay[*4]

[*1]Assistant Professor, Department Of CSE (AI & ML), ACE Engineering College, India.

[*2,3,4]Students of Department Of CSE (AI & ML), ACE Engineering College, India.

DOI: https://www.doi.org/10.56726/IRJMETS72738

ABSTRACT

This research proposes a student assessment model that predicts Intelligence Quotient (IQ) using machine learning techniques. The model combines academic records, professor evaluations, and socio-economic factors to offer a holistic view of student potential and placement readiness. Data includes GPA, subject marks, problem-solving abilities, participation, parental education, and support systems. Quantitative reasoning and degree certifications were rated on a 1–10 scale. Multiple machine learning algorithms were trained and compared to identify the most accurate predictor of IQ levels (scaled 0–3) and salary expectations. The model aims to determine key factors influencing student placement and provide companies with a data-driven tool to enhance hiring while guiding students toward industry-aligned skill development.

Keywords: Intelligence Quotient (IQ), Student Assessment, Academic Performance, Machine Learning, Data Mining.

I. INTRODUCTION

Educational systems traditionally focus on academic scores, often neglecting cognitive abilities, emotional intelligence, and socioeconomic factors. This leads to an incomplete assessment of student potential and job readiness. To bridge this gap, the project introduces a machine learning-based IQ assessment model that integrates academic records, professor evaluations, and family background. It evaluates attributes like quantitative reasoning and certifications on a standardized scale. Advanced algorithms such as Cat Boost, Extra Trees, MLP Classifier, Naive Bayes, and LDA are used for accurate and unbiased predictions. The model not only measures IQ but also predicts salary ranges and identifies key factors influencing placement, helping companies hire better and educators support students more effectively.

II. LITERATURE SURVEY

[1]. Predicting Student Performance Using Machine Learning Techniques

R. Baker et al. (2022) present a comprehensive analysis of machine learning techniques, such as decision trees, support vector machines, and neural networks, for predicting student academic performance. The study highlights the importance of feature selection, including IQ levels, learning habits, and attendance, for accurate predictions.

[2]. Adaptive E-Learning Systems Using Artificial Intelligence

J. Smith and K. Patel (2023) explore AI-based adaptive learning systems that adjust course material based on student profiles, including IQ, learning speed, and past performance. The research demonstrates that adaptive systems enhance learning outcomes and provide personalized feedback.

[3]. Neural Networks for Intelligence and Behavioral Analysis in Education

A. Kumar and P. Wang (2021) introduce a neural network model for analyzing student intelligence and behavioral patterns to predict educational outcomes. Their study integrates psychological assessments and cognitive metrics to create a holistic student model.

[4]. Machine Learning Applications in Educational Psychology

S. Lee et al. (2020) discuss the role of machine learning in educational psychology, focusing on clustering and classification algorithms for grouping students based on IQ, learning preferences, and motivation. The study emphasizes the potential of these techniques in tailoring curriculum design.

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issu:04/April-2025 Impact Factor- 8.187 www.irjmets.com

[5]. An Ensemble Approach for Student Performance Prediction

H. Zhang et al. (2024) propose an ensemble machine learning approach combining random forests and gradient boosting for predicting student performance. The study highlights that incorporating IQ scores as a key feature significantly improves model accuracy and interpretability.

III. EXISTING MODEL

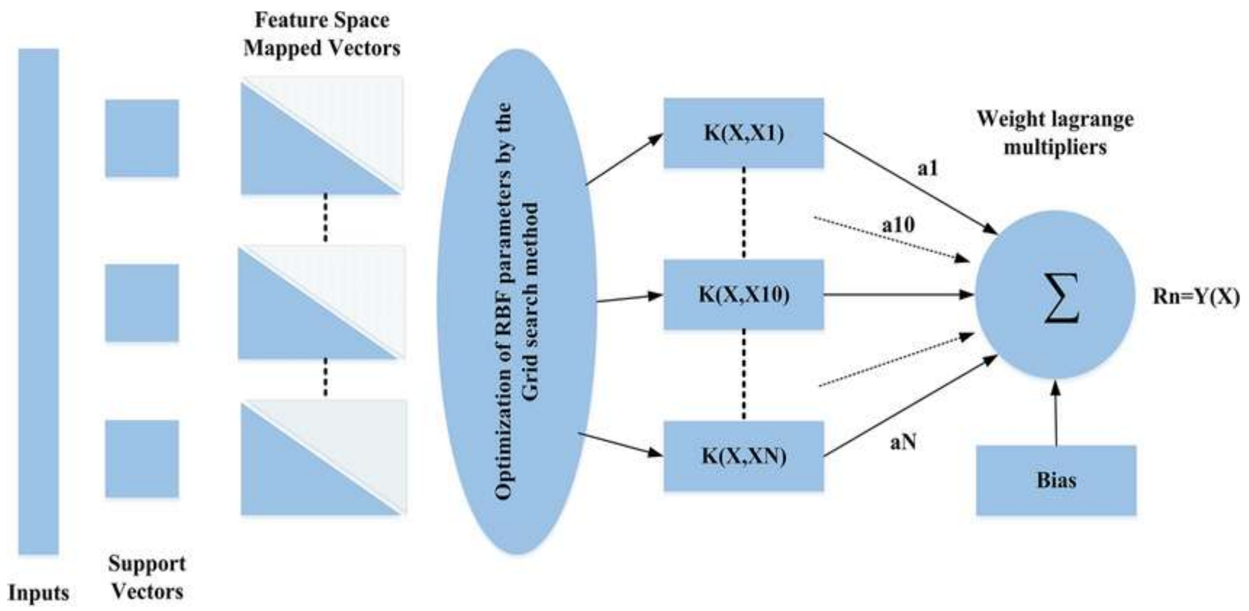
In today's educational system, student assessment largely depends on standardized and traditional IQ tests like the Wechsler, Stanford-Binet, and Raven's Progressive Matrices. These tests, often paper-based and conducted under supervision, provide a single IQ score from limited scenarios. Intelligence is typically evaluated through manual psychometric testing by professionals, which is time-consuming, costly, and difficult to scale for large populations.

Academic performance—mainly grades and exam scores—is also heavily used to judge potential, often ignoring key cognitive traits like creativity, adaptability, and emotional intelligence. The system applies a one-size-fits-all model, overlooking individual learning styles and socio-economic differences, leading to biased outcomes. Moreover, traditional methods lack data-driven insights and fail to recognize non-traditional talents. There is also no continuous feedback loop to track or reassess a student's cognitive development over time.

IV. PROPOSED SYSTEM

The proposed system aims to build a machine learning-based assessment model that predicts a student's Intelligence Quotient (IQ) and offers insights into their cognitive abilities, learning styles, and academic potential. This data-driven model enhances traditional assessments by providing a more personalized evaluation of student capabilities. The system begins with a data collection module that gathers information from IQ tests, academic records, behavioral traits, and psychometric evaluations, incorporating features such as age, gender, study habits, memory skills, and problem-solving abilities. After collection, the data undergoes preprocessing and feature engineering to clean, normalize, and select the most relevant attributes. In the model development phase, machine learning algorithms like Decision Trees, Random Forests, Support Vector Machines, and Neural Networks are tested to identify the most accurate predictor. The trained IQ prediction engine classifies students into IQ bands (e.g., below average, average, above average, gifted) and provides interpretative insights into their strengths and areas for improvement. The results are displayed through a user-friendly dashboard that offers IQ scores, key contributing factors, personalized learning suggestions, and potential career pathways. To ensure reliability, the model is continuously evaluated using performance metrics such as accuracy, precision, recall, and F1-score, with cross-validation and hyperparameter tuning employed to enhance overall performance and generalizability.

V. ARCHITECTURE



Support Vector Regression (SVR) is an extension of Support Vector Machines (SVM) for regression problems. It aims to find a function that approximates the relationship between input variables and a continuous output, with a tolerance for error (ε-insensitive loss).

1. Input and Support Vectors

Given a set of training data, SVR identifies a subset of critical data points called **support vectors**. These points lie closest to the decision boundary and significantly influence the model's predictions.

2. Kernel Function and Feature Mapping

SVR uses a **kernel function** to map input data into a higher-dimensional feature space where a linear relationship can be established. The **Radial Basis Function (RBF)** kernel is commonly used to handle nonlinear patterns:

$$K(x, x_i) = \exp(-\gamma \|x - x_i\|^2)$$

3. Optimization

Model parameters, including the penalty term (C) and the RBF parameter (γ), are optimized using **grid search** to minimize prediction error and avoid overfitting.

4. Prediction Function

The SVR model predicts outputs using the following decision function:

$$f(x) = \sum_{i-1}^{n} \alpha_i K(x, x_i) + b$$

where:

- αi are the Lagrange multipliers (weights),
- $K(x,xi)$ is the kernel function,
- b is the bias term.

5. Output

The final output is a continuous value f(x)$f(x)$, representing the predicted regression value for the given input xx.

VI. ALGORITHM

Step-1: Data Collection: Gather student-related data including academic scores, behavioral traits, psychometric evaluations, and socio-economic background. Key features include GPA, memory skills, reasoning ability, and parental education.

Step-2: Data Preprocessing: Clean and normalize the data. Handle missing values, encode categorical variables, and scale numerical features using standard techniques such as Min-Max Scaling or Standardization.

Step-3: Feature Selection: Use correlation analysis, mutual information, or domain knowledge to select the most relevant features that influence IQ scores, improving model performance and interpretability.

Step-4:Train-Test Split: Split the dataset into training and testing sets, typically in a 80-20 or 70-30 ratio, to train the model and validate its performance on unseen data.

Step-5: Train the SVR Model: Implement Support Vector Regression with a suitable kernel (e.g., RBF or Polynomial). Use cross-validation and hyperparameter tuning to optimize parameters such as C, epsilon, and kernel.

Step-6: Evaluate the Model: Measure model performance using evaluation metrics such as Mean Squared Error (MSE), R^2 score, and Mean Absolute Error (MAE) to assess prediction accuracy and generalization ability.

VII. CONCLUSION

The proposed IQ-based student assessment model effectively integrates academic, behavioral, and socio-economic factors to deliver a comprehensive evaluation of a student's cognitive potential. By leveraging machine learning algorithms—particularly Support Vector Regression (SVR)—the model offers accurate IQ predictions and valuable insights into students 'strengths, weaknesses, and placement readiness. This data-driven approach not only enhances traditional assessment methods but also assists educators and recruiters in making informed decisions. Ultimately, the system aims to bridge the gap between student capabilities and industry expectations, promoting equitable opportunities and personalized learning pathways

VIII. REFERENCES

[1] A. Abramovitch, G. Anholt, S. Raveh-Gottfried, N. Hamo and J. S. Abramowitz, "Meta-analysis of intelligence quotient (IQ) in obsessive-compulsive disorder", Neuropsychol. Rev.,vol. 28, no. 1, pp. 111-120, Mar. 2018.

[2] N. A. Goriounova, D. B. Heyer, R. Wilbers, M. B. Verhoog, M. Giugliano, C. Verbist, et al."Large and fast human pyramidal neurons associate with intelligence", eLife, vol. 7, Dec. 2018.

[3] A. Gibbons and R. T. Warne, "First publication of subtests in the Stanford-binet 5 WAIS-IV WISC-V and WPPSI-IV", Intelligence, vol. 75, pp. 9-18, Jul. 2019.

[4] S. Khan, "A comparative analysis of emotional intelligence and intelligence quotient amongSaudi business students 'toward academic performance", Int. J. Eng. Bus. Manage., vol. 11, Oct. 2019.

[5] R. Jiang, V. D. Calhoun, L. Fan, N. Zuo, R. Jung, S. Qi, et al., "Gender differences in connectome-based predictions of individualized intelligence quotient and sub-domain scores", Cerebral Cortex, vol. 30, no. 3, pp. 888-900, Mar. 2020.