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Title **Deep Learning Model for University Students GPA Prediction with Placement Assistance**

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Deep Learning Model for University Students GPA Prediction with Placement Assistance

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ABSTRACT:

In higher educational institutes, many students need to war tough to finish one-of-a-kind publications for the reason that there's no devoted guide supplied to college students who want unique interest in the registered publications.Predicting the performance of studentsis one of the most critical topics required for studying contexts including colleges and universities, as it allows to layout a hit mechanisms that improve tutorial outcomes and save you dropouts amongst various items.

Current methods of college students' Grade Point Average (GPA) prediction rely on the use of tabular facts as input. Intuitively, inclusive of historical GPA facts can help to enhance the performance of a GPA prediction version. In this look at, we gift a dual-enter deep studying version this is capable of simultaneously manner time-series and tabular records for predicting student GPA. Our proposed model achieved the satisfactory ordinary performance among all tested fashions with 0.4142 MSE (Mean Squared Error) and 0.418 MAE (Mean Absolute Error) for GPA with a four.0 scale. It additionally has thewonderful R2-rating of 0.4879, which approach it explains the proper distribution of college students' GPA better than different models.

The purpose of any new technology is to make people life easier this application can be esaily implimented under various situations. As an extention of this project we can implement concept of advance learning models such as MLP classifier,ISTM,RNN models and creating an application for the model to make it advanced.

After the prediction the gpa of the students we can use that prediction for assistance using placements like the particular student with specific skills can be estimated to be placed in any company with the specific requirements.

Keywords: Grade point avarage (GPA), MSE (Mean Squared Error), MAE (Mean Absolute Error)

INTRODUCTION:

Machine learning techniques can be utilized for students' grades prediction in different courses. Such techniques would help students to improve their performance based on predicted grades and would enable instructors to identify such individuals who might need assistance in the courses. To measure the academic performance, the Grade Point Average (GPA) is commonly used. The result of academic productivity via GPA values can provide a more straightforward approach to measure the students' satisfaction that includes environmental, academic, social, cultural, economic, and health aspects.

A Necessity of providing well-targeted academic consultation services ineducational sectors becomes one of the major concerns in improving the quality of school and academic institutions. One of the most important features of such services is the use of educational data mining of student's academic performance, which is capable to reveal latent information that can improve the existing educational system within the institution. For instance, a predictive model can be employed by a university to forecast students' future academic performance, such that the university can identify the students that may have a poor grade. Thus, the university can foster them to have better academic performance, which leads to the improvement of the overall students' performance. Moreover, the accurate prediction of students' academic performance is also an effective strategy for student recruitment, admission, retention, and individualized educational support throughout a students' studies. To measure the academic performance, the Grade Point Average (GPA) is commonly used. The result of academic productivity via GPA values can provide a more straightforward approach to measure the students' satisfaction that includes environmental, academic, social, cultural, economic, and health aspects. Numerous studies have been conducted to develop a prediction model for student GPA. In many studies, the input to the prediction model is tabular data.

Alternatively, historical GPA data can also be employed. Structurally, historical GPA data can be categorized as time-series data, which has different nature than tabular data. An example of study that employed historical GPA is the study by Patil et al. Furthermore, the combination of both tabular and historical GPA data has been proven to be beneficial by Iqbal et al. However, Iqbal et al. treat the historical GPA data as tabular data instead of time-series data, which is its most natural form. We argue that such a treatment removes useful information from the historical GPA data. Thus, in this study,we propose a model that can combine tabular data and historical GPA as time- series data for GPA prediction. The proposed model is a dual-input deep learning model that can take both tabular and time-series data as input simultaneously. The model consists of a Multi-Layer Perceptron (MLP) branch and a Long Short-Term Memory (LSTM) branch which are concatenated for a single GPA prediction.

As an important step to achieving personalized education, academic performance prediction is a key issue in the education data mining field. It has been extensively demonstrated that academic performance can be profoundly affected by the following factors:

- Students' Personality (e.g., neuroticism, extraversion, and agreeableness)
- Personal Status (e.g., gender, age, height, weight, physical fitness, cardiorespiratory fitness, aerobic fitness, stress, mood, mental health, intelligence, and executive functions);
- Lifestyle Behaviors (e.g., eating, physical activity, sleep patterns, social tie, and time management); and
- Learning Behaviors (e.g., class attendance, study duration, library entry, and online learning).

RELATED WORKS:

BEHAVIORAL CHANGE-LINEAR (BC-LINEAR): Traditionally, behavioral change is mainly quantified by two linear metrics: behavioral slope and behavioral breakpoint. First, the behavioral slope can be captured by computing the slope of the behavioral time series of each student using a linear regression. The value of the slope indicates the direction and strength of the behavioral changes, e.g., a positive slope with a greater absolute value indicates a faster increase in behavioral change. Given a mid-term day during the semester, both the pre-slope and post-slope can be calculated to represent the students' behavioral change during the first and second halves of the semester, respectively. Second, the behavioral breakpoint can be captured by computing the rate of behavioral changes occurring across the semester. The value of the breakpoint identifies the day during the semester before and after which a student's behavioral patterns differed. Two linear regressions can be used to fit a behavioral time series and then use the Bayesian information criterion (BIC) to select the best breakpoint. If a single regression algorithm is selected, the breakpoint can be set to the last day.

BEHAVIORAL CHANGE-NONLINEAR (BC-NONLINEAR): In recent years, nonlinear metrics have been increasingly applied to time series analysis. Regarding the students' behavioral time series, nonlinear metrics have been used to discover nonlinear behavioral patterns. We consider entropy an example. In entropy is proposed to quantify the regularity/orderliness of students' behaviors, and it was demonstrated that a small entropy value generally leads to high regularity and high academic performance. Another example is entropy calculated based on a Hidden Markov Model (HMM) analysis which is called HMM-based entropy for simplicity in our study. HMM-based entropy is proposed to quantify the uncertainty/diversity of students' behaviors, e.g., the uncertainty between the transition of different behaviors and the various activities that a behavior exhibits. In HMM-based entropy is evaluated by the following two steps: (i) extracting the hidden states of a behavioral time series by HMM; and (ii) subsequently calculating the HMM-based entropy of the extracted hidden states

Bharadwaj and Pal (2011a) used EDM to evaluate student performance among 300 students from five different colleges who were enrolled in an undergraduate computer application course. The study employed a Bayesian classification scheme of 17 attributes, of which student performance on a senior secondary exam, residence, various habits, family's annual income, and family status were shown to be important parameters for academic performance. In a subsequent study, Bharadwaj and Pal (2011b) constructed a new data set with the attributes of a student attendance and test, seminar, and assignment scores in order to predict academic performance. Meanwhile, Ramaswami and Bhaskaran (2009) compared various feature selection methods for obtaining the best feature combination for improving prediction accuracy. Their data set included several interesting features such as student vision, eating habits, and family attributes.

SYSTEM ANALYSIS:

Existing System

Machine learning techniques can be utilized for students' grades prediction in different courses. Such techniques would help students to improve their performance based on predicted grades and would enable instructors to identify such individuals who might need assistance in the courses. A predictive model can be employed by a university to forecast students' future academic performance, such that the university can identify the students that may have a poor grade. Thus, the university can foster them to have better academic performance, which leads to the improvement of the overall students' performance. Moreover, the accurate prediction of students' academic performance is also an effective strategy for student recruitment, admission, retention, and individualized educational support throughout a students' studies.

To measure the academic performance, the Grade Point Average (GPA) is commonly used. The result of academic productivity via GPA values can provide a more straightforward approach to measure the students' satisfaction that includes environmental, academic, social, cultural, economic, and health aspects. Numerous studies have been conducted to develop a prediction model for student GPA. In many studies, the input to the prediction model is tabular data.

Alternatively, historical GPA data can also be employed. Structurally, historical GPA data can be categorized as time-series data, which has different nature than tabular data.

Proposed System

We present a dual-input deep learning model that is able to simultaneously process time-series and tabular data for predicting student GPA. For a deep learning model to process time-series data Long Short-Term Memory (LSTM) layer is commonly employed. LSTM is a special form of Recurrent Neural Network (RNN), a deep learning layer that takes input from the previous time-step when processing the current timestep. LSTM improves standard RNN with better long-range dependencies modeling. In addition to that

we are also using random forest classifier to predict that particular student is placed in which company according to the requirements of the company and skills of the student. And also, finally we are gifting a GUI application for this model so that the prediction will be crystal clear.

SYSTEM DESIGN:

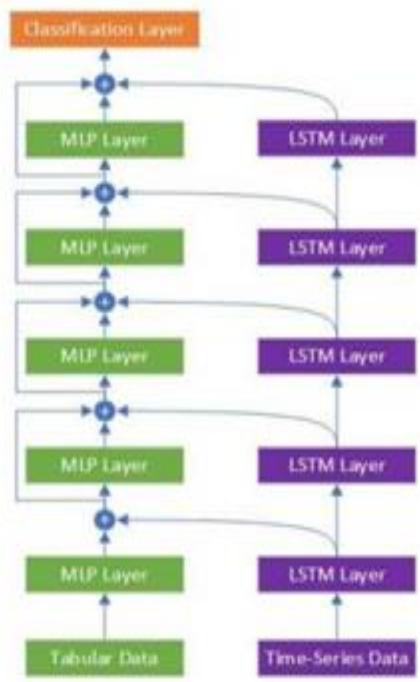

Fig 1: Data Flow Diagram

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```
[1, 98, 97, 92, 94, 91, 90, 21]
[2, 56, 67, 78, 67, 89, 70, 28]
[3, 45, 57, 64, 85, 3, 86, 27]
[4, 35, 68, 84, 68, 63, 67, 27]
[5, 85, 94, 63, 85, 98, 56, 8]
```

Fig 3: Predicting the final company

RESULTS:

```
Enter no.of subjects : 6
Enter no.of students : 5
Enter Student ID : 1
Enter Marks : 98
Enter Marks : 97
Enter Marks : 92
Enter Marks : 94
Enter Marks : 91
Enter Marks : 90
Enter Student ID : 2
Enter Marks : 56
Enter Marks : 67
Enter Marks : 78
Enter Marks : 67
Enter Marks : 89
Enter Marks : 70
Enter Student ID : 3
Enter Marks : 45
Enter Marks : 57
Enter Marks : 64
Enter Marks : 85
Enter Marks : 3
Enter Marks : 86
Enter Student ID : 4
Enter Marks : 35
Enter Marks : 68
Enter Marks : 84
Enter Marks : 68
Enter Marks : 63
Enter Marks : 67
Enter Student ID : 5
Enter Marks : 85
Enter Marks : 94
Enter Marks : 63
Enter Marks : 85
Enter Marks : 98
Enter Marks : 56
[[1, 98, 97, 92, 94, 91, 90],
 [2, 56, 67, 78, 67, 89, 70],
 [3, 45, 57, 64, 85, 3, 86],
 [4, 35, 68, 84, 68, 63, 67],
 [5, 85, 94, 63, 85, 98, 56]]
```

Fig 2: Taking input from the user

```
Marks=[98. 97. 92. 94. 91. 90.], GPA=[9.297971]

Percentage = [88.33072]
Marks=[56. 67. 78. 67. 89. 70.], GPA=[7.17462]

Percentage = [68.15889]
Marks=[45. 57. 64. 85.  3. 86.], GPA=[5.734625]

Percentage = [54.478935]
Marks=[35. 68. 84. 68. 63. 67.], GPA=[6.468076]

Percentage = [61.446724]
Marks=[85. 94. 63. 85. 98. 56.], GPA=[8.096501]

Percentage = [76.91676]
[88.33071899414062, 68.15888977050781, 54.478935
```

Fig 2: Predicting the individual GPA

Fig 4: GUI output 1

Fig 5: GUI output 2

RESULTS ANALYSAS:

Test Case ID	Test Case Name	Test Case Description	Test Steps			Test Case Status	Test Priority
			Step	Expected	Actual		
01	Start the Application	Host the application	If it doesn't	We cannot	The application	High	High

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		and test if it starts making sure the required software is available	Start	run the Application.	hosts success.		
02	Home Page	Check the deployment environment for properly loading the application.	If it doesn't load.	We cannot access the Application.	The application is running successfully .	High	High
03	User Mode	Verify the working of the application in freestyle mode	If it doesn't Respond	We cannot use the Freestyle mode.	The application displays the Freestyle Page	High	High
04	Data Input	Verify if the application takes input and updates	If it fails to take the input or store in The Database	We cannot proceed further	The application updates the input to application	High	High

CONCLUSION:

As this study illustrated, several data mining prediction techniques can accurately predict student GPA at graduation well in advance, which can identify students needing extra help to improve their academic performance and, in turn, their GPAs at graduation. In addition to that we are also using random forest classifier to predict that particular student is placed in which company according to the requirements of the company and skills of the student. And also, finally we are gifting a GUI application for this model so that the prediction will be crystal clear. And also we created our model in such a way thatit can predict GPA and company name of multiple students based on the input given.

The future scope of our model is to divide the students based on their GPA and classify them accordingly such that the particular student with a specific percentage will be eligible to that company. Also, we can predict where the particular student is lagging and how they can improve their skills and get placed in companies with higher packages. Thus if all the updates are implemented, then we may run successfully in predicting the companies.

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