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PMSIEMDL: Design of a Pattern analysis Model for identification of Student Inclination towards different Educational-fields via Multimodal Deep Learning Fusions

Abstract: - Identification of student inclination towards different educational fields requires integration of deep pattern learning models with temporal data analysis techniques. These techniques are highly context sensitive, and cannot be scaled for analysis of students that have an interest in multiple domains. Moreover, existing deep learning models are highly complex, and showcase moderate performance when used on real-time datasets. To overcome these limitations, this text proposes design of a Pattern analysis Model for identification of Student Inclination towards different Educational-fields via Multimodal Deep Learning fusions. The proposed model initially collects data samples from a large number of students, and segregates them into different classes. These include social data, personal habits data, education data, family related data, performance data and future inspiration data classes. These datasets were combined with a customized psychological questionnaire which was curated by experts in the field of student counselling & psychology. Based on student responses, their entity specific classes were generated, that were separately trained via different Convolutional Neural Network (CNN) Models, which assists in identification of student-performance at individual-class levels. These performances are compared with existing inclination datasets via a fusion of Long-Short-Term Memory (LSTM) & Gated Recurrent Neural Network (GRNN), which assists in identification of correlation between subject-level inclinations & their entity classes. This provides with a probabilistic map of different subjects towards which the student might be inclined, and assists them to select their study streams. The generated map was validated for multiple students, and recommendations were made based on higher probability values, which assisted in identification of student inclination levels. The model was evaluated under large datasets and its performance was compared with various state-of-the-art methods under different scenarios. Based on this comparison, it was observed that proposed model was capable of achieving 8.5% better recommendation accuracy, 4.9% higher prediction precision, 6.5% better recommendation recall & 2.9% better Area Under the Curve (AUC) levels, which makes it highly useful for a wide variety of student inclination use cases.

Keywords: Student, Behaviour, Inclination, Study, Accuracy, Psychology, Social, CNN, GRNN, LSTM, Habits, Family, History

I. INTRODUCTION

Student behaviour analysis for study-based inclination prediction is a complex task that requires collection of multidomain datasets, their pre-processing & filtering, student-specific feature representation, identification of optimal feature sets, temporal classification of these sets, and their post-processing analysis. Such models require differential analysis with existing student behaviour datasets, which assists them in comparatively evaluating optimum inclination levels for different fields of study. A typical analysis model [1] that uses a combination of multidomain datasets with Convolution Neural Networks (CNNs), and Genetic Optimizations is depicted in figure 1, where in data from social media, Psychological Questions, Interest Details, Family History & Subject Wise performance are analyzed to identify inclination levels.

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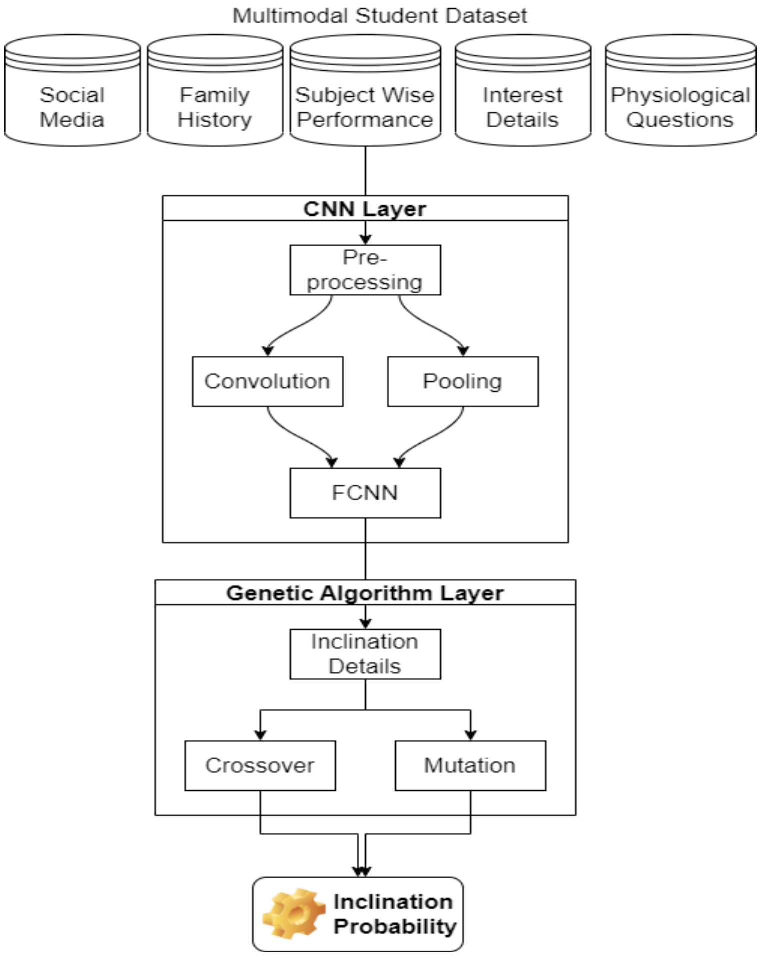

Figure 1. A typical inclination model based on temporal performance & bioinspired computing processes

The model uses bioinspired layer to optimize the parameters used during inclination identification process, which makes the model highly functional and useful for low-delay and high accuracy use cases. Similar models [2, 3, 4] that use Generative Adversarial Networks (GANs), Q-Learning, and other deep learning methods are discussed in the next section of this text. This section describes the models in terms of their functional nuances, contextual advantages, application-specific limitations, and operational future research scopes. These models cannot be scaled for analysis of students who have interests in multiple domains because, according to this analysis, they are very context-sensitive. Furthermore, when applied to real-time datasets, these deep learning techniques perform only moderately well due to their high complexity. Section 3 suggests creating a pattern analysis model for identifying student preferences for various educational fields using multimodal deep learning fusions in order to get around these limitations. In order to determine the proposed model's real-time performance levels, it was evaluated in terms of recommendation accuracy, prediction precision, recommendation recall, and Area Under the Curve (AUC) levels, and compared with various state-of-the-art methods. Finally, this text offers some insightful conclusions about the suggested inclination-prediction model and suggests ways to further enhance its functionality in various scenarios.

II. LITERATURE REVIEW

Domain-specific data are required for training and validation of student behaviour analysis. Social networking, retail, online learning and other businesses may benefit from custom app-based solutions that make data collecting easier. As a result of the CoVID pandemic, a growing number of students are taking online courses, which has facilitated the collection of data more quickly. Single, dual, and multimodal methods are used to measure student participation in [1]. Keystrokes and mouse movements are used to anticipate the user's emotional state as well as their typing pace. Using Mini Xception Nets, it is possible to assess student participation. Despite the model's high computing cost and modest latency, it obtains an accuracy of 95.23 percent. The best writing classification performance is provided by the Nave Bayes (NB) model. The NB model may also be used for reading, viewing videos, and other activities. A variety of application-specific conditions may benefit from this method. The system's total effectiveness may be improved if the NB model is used in [2] along with features such as online teaching design relevance, delivery quality, online assistance, student engagement, and contingency modelling. This strategy relies on simple machine learning models like random forests to achieve mediocre accuracy while requiring a sophisticated implementation. According to [3], the behavioural, cognitive, social and emotional elements of this paradigm are studied in detail. Work in [3] shows a bi-factor structural equation modelling exploratory investigation (BESEM). This approach uses correlations between characteristics to determine the value of an interaction. The model has a 98.2 percent accuracy rate, a 0.05 MSE, and a considerable delay in the prediction of results. In comparison, ICMCFA's 96.4 percent accuracy, 0.07 MSE, and high latency are all below BCFA's 96.4 percent accuracy, while ESEM's 98.3 percent accuracy, 0.09 MSE, and exorbitant delay are all above this one. Real-time school and college applications are possible because to high performance. To find patterns, [4] looks at general, social, and psychological behaviour, as shown in [4]. Clustering monthly consumption, meals, work, relaxation, the internet and exercise as well as class attentiveness and book borrowing as adaptive k Means is used in the model (AKM). Students may be divided into three categories depending on their schedules and eating habits using this information. There is a 94 percent level of accuracy, however the model suffers from a substantial amount of computing time. The validation performance of over 550 pupils [5] may be improved by quantifying and studying this efficiency. Other approaches for assessing student behaviour are available in the research, such as ITT and 2SLS. 2SLS has intermediate accuracy and high delay, whereas ITT has poor accuracy and moderate latency.

The Mooring Model and student learning factors are examined in [6]. The model examines student behaviour based on learning comfort, perceived security risk, service quality, ease of use, usefulness, task technology fit, teacher attitude, habits, and switching costs. Work in [6] depicts the relationship between a student's desire to move schools and other attributes. The accuracy of the model is above 93%, and it has a low error rate and a short latency. Monitor students' willingness to adopt online learning systems using the Technology Acceptance Model [7]. (TAM). Perceived usefulness, perceived ease of use and attitude toward use are all taken into account when evaluating student behaviour. Student interest in online learning may be gauged by looking at the model's 10 connection weights. The algorithm is 91.5 percent accurate in predicting user behaviour, but it needs a large amount of data to do so. Since data collection is straightforward, the concept may be used to studying children who have unusual abilities. It is discussed in [8] how G&T students in Australia might have a bright future in STEM fields. Model investigates rural students' behaviour using machine learning and local knowledge as a starting point (LK). The 90 percent accuracy, low MSE, and short latency of the model make it useful in a wide range of situations.

An effective method for behaviour analysis may be achieved by combining the models from [7] and [8]. Students from rural regions around the country are being studied in [9] to see how hybrid models' function. In order to evaluate achievement gaps, the study examines rural children's chances, ambitions, difficulties, and obstacles. Data from WoS, IFPRI library, MDPI, CAB abstracts, and other sources are analyzed in this task. The majority of rural youngsters want a better education and higher education by moving to the city. Mobile learning systems, which may be given via smartphone-based technology [10], are needed to provide such opportunities, and records from rural and urban schools can be linked to develop an effective learning model. The BISM approach uses focus groups, pre- and post-test situations, and basic analysis to estimate student behaviour. High latency and MSE limits the model's 89 percent accuracy across student groups. Socio-economic factors such as socioeconomic class, ethnicity and gender are also important to include while doing social behavioural analysis [11]. Machine learning (MLM) models with high accuracy and low error rates but large latency may be trained using these parameters [11].

In [12, 13 and 14], we discuss how to do multiple person behaviour analysis, classroom behaviour analysis and learning pattern analysis. In order to achieve a fair level of accuracy, these models make use of data usage, in-class and online behaviour analysis. Multi-user fitness coach model [12] achieves 85 percent accuracy with moderate error and high delay, while Online Hard Example Mining (OHEM) RCNN (94 percent accuracy) with very high delay and low error and Felder and Silverman learning style model (FSLSM) [14] with decision tree classifier achieve 85.7 percent accuracy (DT). Both models exhibit significant errors and delays as a result of the increased amount of training data. By combining these two models, the MSE will be reduced, and response time will be sped up. Thus, they may be used in a wider range of situations. These models are used to study student behaviour in group presentations by [15]. The approach assesses student performance based on a variety of cues, including body language, posture, eye contact, speaking pace, and other factors. Over 83% accuracy is achieved with significant latency and high MSE owing to location and other body parameter variations, thanks to these factors. An operating system for behavioural analysis (OS) is suggested by [16]. (BAOS). For this, the OS model makes use of many metrics such as login time, log size, and file open counts, amongst others. It was evaluated on 850 students and determined to be 75% accurate due to the wide variety of data included in the research. Clustering online learning sets into groups, such as the one in [17], may improve efficiency. Maps (SOMs) and neural networks (SOMNNs) can do this. 1.7 million data points were analyzed using parameters such as grades, test scores, and continuing assessments. It was determined that 93.61 percent accuracy in metrics such as assignment submissions, resources created, posts made, and pages seen made the system usable in real time. Although multiple parametric selection minimizes MSE, complexity creates significant processing delays.

Sakai LMS is used as an example in [18] to suggest another LCA-based method. The 93 percent accurate model evaluates resource utilization, lesson evaluation, tests, surveys, and assignments, among other things. Gradient Boosted Decision Tree (GBDT) model evaluates and classifies various data features, resulting in small latency and low MSE. GBDT. [19, 20, 21] also propose similar models that use k Means, MFR model, and TeSLA to assess student behaviour during the current CoVID outbreak. [19, 20, 21] (Adaptive Trust-based e-Assessment System for Learning). Models like this are useful for predicting student behaviour and may be used in a variety of settings. k Denotes a 66.5 percent accuracy rate, a 72 percent MFR rate, and an 89.2 percent TeSLA rate. Improved accuracy and generality are gained by combining these models. Structured Equation Modelling (SEM) and association rule mining using apriori may help improve the accuracy of these models. For optimizing present systems, the EENN and SEM models have minimum complexity and a moderate MSE, making them beneficial. While the apriori model has an accuracy rate of 84.75% when applied to a dataset, how it is applied depends on the dataset.

It may be possible to predict student conduct by analysing student feedback in [25], an adaptive feedback system is used for collaborative behaviour analysis. There is an 83 percent accuracy rate in the model's performance monitoring, behaviour and engagement analysis, and suggestive analysis. Learning management systems, deep knowledge tracing with many features, and integrated learning techniques all have the potential to improve this accuracy. In order to achieve 91% accuracy with modest latency and MSE, LMSM makes advantage of online behavioural factors such as connection distribution, average lecture time, average number of sessions, and so on. This model uses a neural network (RNN) for analysis of skill, response time, practice sets and beginning action type among other things. In various student behaviour analysis contexts, the DKTMFAM model has an accuracy rate of 98 percent. The MSE is 0.2, which is higher than some other models, and the LSTM and other RNN components make training and validation take a long time. To achieve 97% accuracy with modest latency and MSE, a GBDT model is trained utilizing study duration (access time), number of posts, etc. To construct an effective student behaviour analysis system, [27] and [28] may be employed.

SRM [31] and DBSCAN with k Means (density-based spatial clustering of applications with noise) [32] are further methods to consider. This set of models is an extension of the previously described models, and they produce great accuracy with a moderate latency and MSE. In terms of accuracy, FGWANN has 96.3 percent, 0.09 MSE and considerable latency, whereas PrefCD has 76.14 percent. It's great for real-time applications since SRM has a 96% accuracy with an MSE of 0.15 and DBkMeans has 91% accuracy with an MSE of 0.15. Some models may help students behave better in certain situations. Student health-related concepts and improved real-time online learning performance are the focus of [33], an example of how mobile health, temporal parameters, and geographic features may be used to benefit students.

Models such as cellular automata (CA), cyber engagement (CE), predictive game theory model (PGTM) for programming students, and profile-based cluster evolution analysis (PBCEA) take incremental inputs. Additives to the equation include depression (35), programming skills (36), and migratory patterns (37). CA, CE, PGTM, and PBCEA can all achieve 79 percent accuracy on a variety of datasets. These models must be combined and applied to deep learning networks in order to create a complete behavioural analysis model. App-specific context behaviours and model thinking approaches as well as disengaged behaviour are all examined in [38, 39 and 40]. The accuracy, MSE, and latency of these techniques are all acceptable when used in the context of a particular application.

III. DESIGN OF THE PROPOSED PATTERN ANALYSIS MODEL FOR IDENTIFICATION OF STUDENT INCLINATION TOWARDS DIFFERENT EDUCATIONAL-FIELDS VIA MULTIMODAL DEEP LEARNING FUSIONS

According to the literature review, it was found that current models cannot be scaled for analysis of students who are interested in multiple domains because they are very context-sensitive. Furthermore, current deep learning models exhibit mediocre performance when applied to real-time datasets due to their high complexity. This section recommends creation of a pattern analysis model for identifying student preferences for various educational fields using multimodal deep learning fusions in order to overcome these limitations. Flow of the model is depicted in figure 2, where it can be observed that the suggested model gathers data samples from a large number of students at first and divides them into various classes. Social data, individual behaviour data, educational data, family-related data, performance data, and classes of future inspiration data are among these. These datasets were combined with a specially created psychological survey that was put together by professionals in the fields of student counselling and psychology.

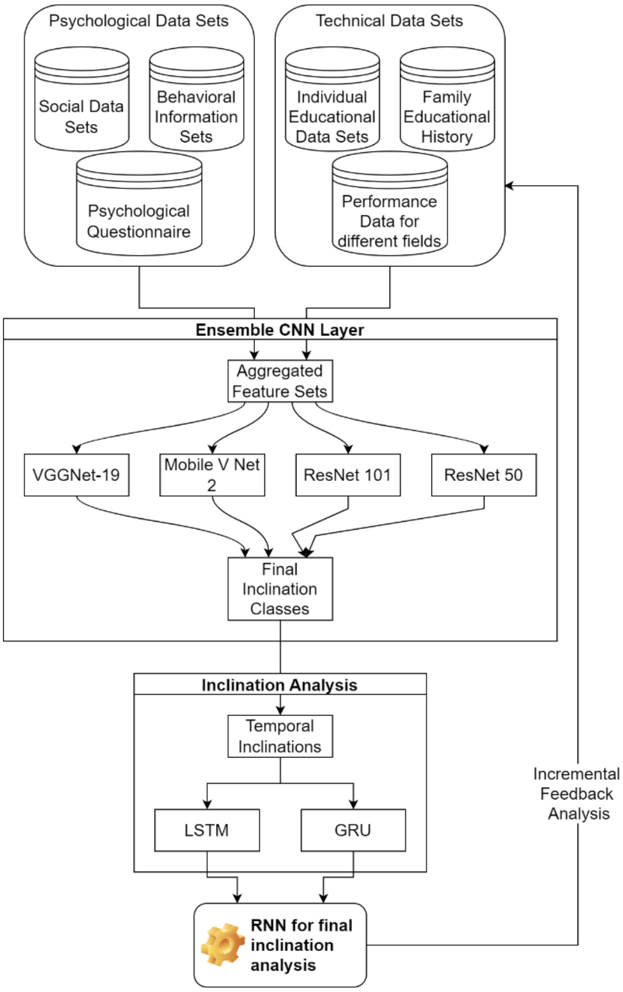

Figure 2. Overall flow of the proposed temporal inclination analysis model with different CNNs & RNN classifiers

Based on the responses from the students, entity-specific classes were created for them, which were then individually trained using various Convolutional Neural Network (CNN) models to help identify student performance at the individual-class level. A combination of Long-Short-Term Memory (LSTM) and Gated Recurrent Neural Network (GRNN) is used to compare these performances with existing inclination datasets and identify any relationships between subject-level inclinations and their entity classes. This gives the student a probabilistic map of the various subjects in which they may have an interest and helps them choose their study areas. Multiple students validated the generated map, and recommendations were made based on higher probability values. This helped to identify the degree of student inclination under multiple scenarios.

The proposed model initially collects following information sets from each of the users,

- Social Data Sets, that includes student’s Tweets, Facebook Posts, LinkedIn activity, etc.
- Behavioural Information Sets, which includes their general social behaviour like number of outings, their friends, type of friends, etc.
- Individual Educational Data Sets, that comprise of their educational preferences and courses done by them during temporal phases of their lives
- Family Educational History, that includes historical datasets about their family’s educational levels.
- Performance Data for different fields, which includes their marks in different subjects and different classes

Along with these datasets, a psychological questionnaire was also created, and given to students for analysis of their current state of inclination in different fields. These questions along with their reasons of selection can be observed from table 1 as follows,

Question (In Regional Languages)	**Reasons for selection**
Your age? (विद्यार्थ्याचे वय)	To check maturity levels
Your location? (विद्यार्थ्याचे राहण्याचे ठिकाण (गाव, तालुका, जिल्हा))	To check exposure levels to different educational fields
Highest education level (विद्यार्थ्याचे उच्चतर शिक्षण)	Identification of educational maturity levels
What interests you most? (Tick everything that is relevant) (आपल्या आवडीचे क्षेत्र (आवडीच्या सर्व क्षेत्रांना टिक करा))	Options like Engineering, Techology, and its applications were presented to identify student’s inclincation towards technological fields
What do you aspire to become? (Tick all that's relevant) (आपल्याला भविष्यात काय बनायला आवडेल?)	Options like Engineer, CA, Lawyer, Doctor, etc. were presented for analysis
Where to you plan to live in future? (आपल्याला भविष्यात कुठे राहायला आवडेल?)	To identify growth mindset of students
What do your parents expect from you? (Tick all that is relevant) (आपल्या पालकांची आपल्याकडून काय अपेक्षा आहे?)	To analyze the type of future they want to build, and their aspirations

Where do you see yourself in next 5 years? (आपण पुढच्या पाच वर्षात स्वतःला कुठे बघता?)	To analyze the type of future they want to build, and their aspirations
Enter some information about your future plans (आपल्या भविष्यातील प्लान बद्दल थोडक्यात लिहा.)	To identify growth mindset & aspirations of students
What is your strength? (Check all that's applicable) (आपली बलस्थाने कश्यात आहे?)	Self-evaluation of students, which will assist in identification of their SWOT (Strengths Weaknesses Opportunities and Threats) Analysis
Which type of classes do you like? (तुम्हाला कोणत्या प्रकारे शिक्षण घ्यायला आवडते?)	Either they are inclined towards online or offline educational modes
	Evaluate if they are friendly with online classes
Do you like playing online games like PUBG?(तुम्हाला पब्जी Pub-G सारखे ऑनलाइन गेम खेळायला आवडतात का?)	Identify their idle mode hobbies
Have you ever tried online payments platform like PhonePe, PayTM or GPay ?(तुम्ही फोन पे, पेटीएम, गुगल पे यांचा वापर करता का?)	To know their technical, know how levels
How you find English as a subject?(इंग्रजी हा विषय आपल्याला कसा वाटतो?)	Evaluate their inclination towards global educational models
Do you think Mathematics is very hard subject? (तुम्हाला गणित विषय खूप कठीण वाटतो का?)	Evaluate their logical skills
In SSC which subject you liked most? (तुम्हाला	Identify their strengths

कोणता विषय सर्वात जास्त आवडतो?)	
Do you have any idea about Polytechnic Education?(तुम्हाला पॉलीटेक्नीक बाबत माहिती आहे का?)	Identify their general purpose know how levels
If yes from whom you came to know about ? (पॉलीटेक्नीक बाबत माहिती असल्यास हि माहिती तुम्हाला कोणाकडून मिळाली?)	Identify their information gathering sources
In your view what is success ? (तुमच्यानुसार यश मिळवले हे कसे सांगू शकाल?)	Check their mindset and therefore analyze their future plans
Do you think polytechnic contains only Mathematics? (पॉलीटेक्नीक हे फक्त गणित विषयावर आधारित आहे असे आपल्याला वाटते का?)	Verify their technical know-how levels
What does your parent do for earning? (तुमचे पालक पैसे कमाविण्याकरिता काय करतात?)	To analyze their family support for higher education levels
Which subject do you think are going to be useful for your future life?(कोणता विषय तुमच्या भविष्यासाठी ठीक आहे असे तुम्हाला वाटते ?)	To identify their inclination towards different educational fields
Do you think homework assignments are necessary for effective learning? (होमवर्क ,असायमेन्ट तुमच्या चांगल्या शिक्षणासाठी चांगले आहे का)	Check lethargy levels of students
Do you think use of	To evaluate their inclination towards

technology is very much needed in learning or general chalk and board system is best? (तुमच्यानुसार शिक्षणामध्ये नवीन नवीन टेक्नोलॉजीचा वापर करणे गरजेचे आहे कि पारंपारिक खडू व फळ्याचीच पद्धत सर्वात चांगली आहे)	technology driven courses

Table 1. Psychological questionnaire and reasons for asking the questions

The datasets from different sources were converted into yearly data batches, and each of these batches were classified via an ensemble CNN model, that combines VGGNet-19, MobileVNet2, ResNet 101 and ResNet 50 models. These models were selected because of their higher accuracy performance under the collected datasets. Each of these models are depicted in figure 3 (a), 3 (b), 3 (c), and 3 (d) respectively, where it can be observed that they combine Convolutional, Max Pooling & Drop Out layers for feature extraction purposes.

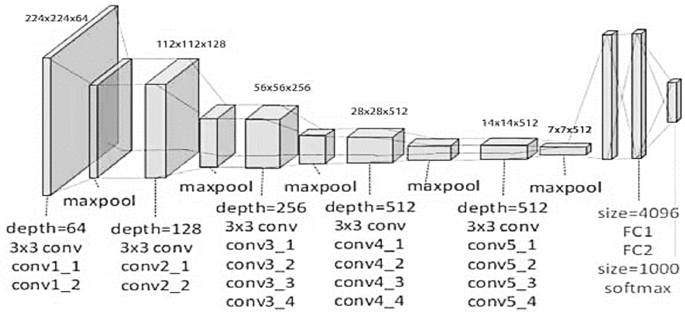

Figure 3 (a). Design of the VGGNet-19 Model for batch-based inclination identification process

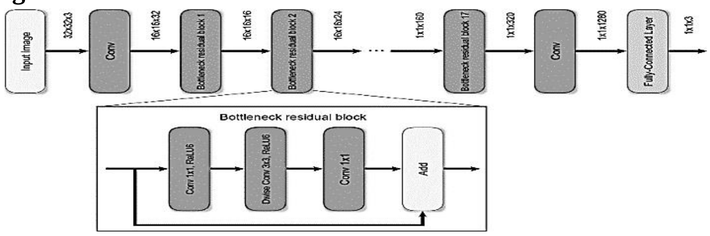

Figure 3 (b). Design of the MobileVNet2 Model for batch-based inclination identification process

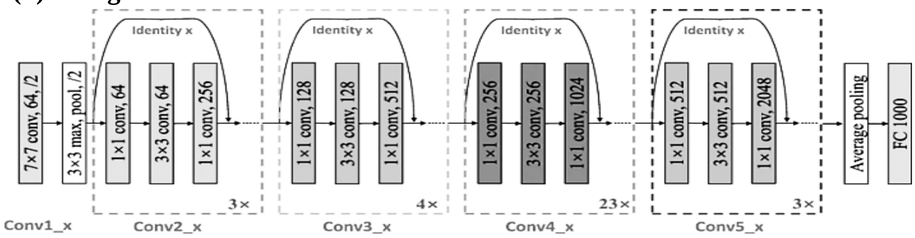

Figure 3 (c). Design of the ResNet101 Model for batch-based inclination identification process

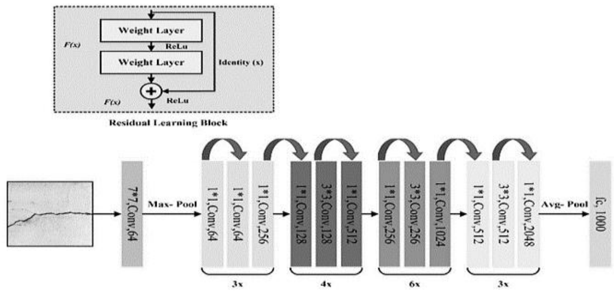

Figure 3 (d). Design of the ResNet50 Model for batch-based inclination identification process

These convolutional features are extracted via equation 1, where a Rectilinear Unit (ReLU) kernel is used for activation of feature sets.

$$Conv_{out_{i,j}} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} \sum_{b=-\frac{n}{2}}^{\frac{n}{2}} SF(i-a, j-b) * ReLU\left(\frac{m}{2}+a, \frac{n}{2}+b\right) \ldots (1)$$

Where, SF represents the student feature vectors, that are represented in 2D for better analysis, while m, n represents different window sizes that are setup by individual CNN layers, while a, b represents padding sizes which are also decided by different contextual CNN layer types. All these features are processed by a Max Pooling layer that assists in removal of redundant feature sets. This is needed because a lot of similar features are extracted by the convolutional layers, which reduces inclination-classification efficiency levels. The Max Pooling layer generates a variance threshold via equation 2, which is used for selection of relevant feature sets.

$$f_{th} = \left(\frac{1}{SF_i} * \sum_{x \in SF_i} x^{p_i}\right)^{1/p_i} \ldots (2)$$

Where, p represents feature variance levels, that is evaluated via equation 3, and assists in identification of deviation levels of extracted feature sets from average feature levels.

$$p = \sqrt{\sum \frac{\left(SF - \sum \frac{SF}{N}\right)^2}{N}} \ldots (3)$$

Where, N represents number of extracted feature sets. Features with levels more than f_{th} are passed to the next convolutional layer, while others are removed due to low variance levels. The selected features are re-convoluted and multiple feature sets are extracted by each of the CNN Models, which are classified via Soft Max based activation layers. These layers use weights (w), and biases (b) in order to categorize student feature sets into temporal classes via equation 4,

$$c_{out} = SoftMax\left(\sum_{i=1}^{N_f} f_i * w_i + b_i\right) \ldots (4)$$

Where, c_{out} represents output classes, while f_i represents extracted feature sets from the convolutional layers. These classes are extracted for each progressive year, and are combined to form a temporal dataset, which is processed via a combination of Long Short-Term Memory (LSTM) & Gated Recurrent Unit (GRU) layers. The combined LSTM & GRU Model is represented in figure 4, which assists in high-density feature extraction from limited temporal inclination-class sets.

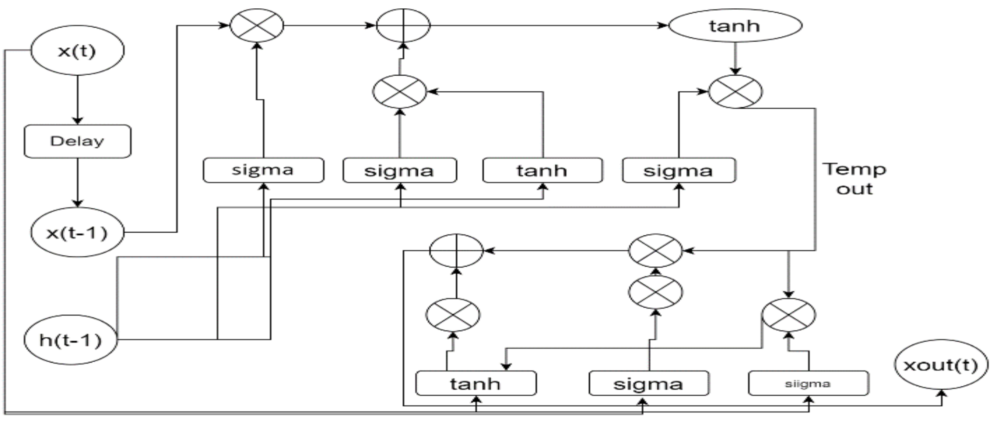

Figure 4. Combination of LSTM & GRU for extraction of high-density temporal sets

Both LSTM & GRU Models are capable of extraction of large feature sets, but a combination of these is used in order to extract high-density cascaded features. These features are useful for analysing temporal inclination classes via Recurrent Neural Networks (RNNs) for estimation of final inclination levels. Along with the temporal classes, responses of the psychological questionnaire are also processed by the LSTM & GRU feature extraction models, thereby assisting in identification of current inclination levels for different student & course types. These models generate an initialization feature vector via equation 5, which combines temporal classes (x_{in}) with a feature kernel matrix (h_t) for augmentation purposes.

$$i = var(x_{in} * U^i + h_{t-1} * W^i) \dots (5)$$

These initialization vectors are further expanded to form forgetting feature sets & output feature sets via equations 6 & 7 as follows,

$$f = var(x_{in} * U^f + h_{t-1} * W^f) \dots (6)$$

$$o = var(x_{in} * U^o + h_{t-1} * W^o) \dots (7)$$

All these features are combined to form temporal LSTM features via equations 8 & 9,

$$C_t' = tanh(x_{in} * U^g + h_{t-1} * W^g) \dots (8)$$

$$T_{out} = var(f_t * x_{in}(t-1) + i * C_t') \dots (9)$$

Based on these features, temporary feature sets were extracted via equation 10 as follows,

$$h_{out} = \tanh(T_{out}) * o \dots (10)$$

These equations use U & W constants, which are continuously tuned by the RNN layer via hyperparameter tuning process. The output features h_{out} are processed by a GRU layer, that initially generates temporary feature sets via equations 11 & 12,

$$z = var(W_z * [h_{out} * T_{out}]) \dots (11)$$

$$r = var(W_r * [h_{out} * T_{out}]) \dots (12)$$

These feature sets are further augmented via tangent activation functions to form final features via equations 13 & 14 as follows,

$$h_t' = tanh(W * [r * h_{out} * T_{out}]) \dots (13)$$

$$xout = (1 - z) * h_t' + z * h_{out} \dots (14)$$

The final output features are classified via a RNN Model that is depicted in figure 5, and uses interim feature sets to generate final output inclination class.

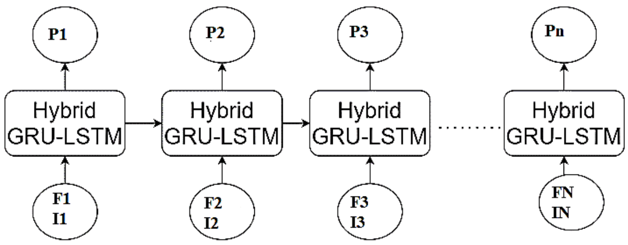

Figure 5. Design of the RNN Layer for generation of probability maps

This class is estimated via equation 15, and uses a Purely Linear Activation function for deployment of a linear classification process.

$$P_{out} = purelin\left(\sum_{i=1}^{N} xout_i * W_i\right) \dots (15)$$

Where, P_{out} represents output probability of inclination towards a particular field, while N represents number of fields that are being analyzed by the model, and W_i represents weights that are being tuned via hyperparameter tuning process. Based on these probabilities, the model is able to generate a probability map, that is used to identify student inclinations towards different study fields. Results of these probability maps were correlated with training & validation sets, and the model was continuously updated via incremental learning operations. To perform this task, an incremental probability correlation level was evaluated via equation 16,

$$Corr_j = \frac{\sum_{i=1}^{N} p(test_i) - p(new_i)}{\sqrt{\sum_{i=1}^{N} p(test_i) - p(new_i)^2}} \ldots (16)$$

Where, $p(test)$ & $p(new)$ represents output probability maps for test & new input sets for different inclination fields. If the value of $Corr < 0.999$, then the new values are added back to the dataset, which assists in improving the dataset size for higher accuracy levels. These accuracy levels were validated on real-time datasets for multiple uses cases. Parameters including accuracy of field identification, precision for inclination identification, recall levels, and delay needed for identification of inclination was evaluated & compared with standard models in the next section of this text.

IV. PERFORMANCE EVALUATION AND COMPARISON

Students' proclivity for engineering, social science, journalism, accounting, and medicine can be assessed using the proposed model that incorporates multimodal datasets with ensemble CNNs & RNN techniques. Over 5000 students' datasets were collected to test the model's performance, and a variety of performance metrics, including accuracy of field identification (AFI), precision of inclination identification (PIA), recall of field identification (RFI), and evaluation delay (DE), were analyzed. A comparison was made between these metrics and BE SEM [3] and TeS LA [19] models. Nearly 60% of the 5000 students were used to train the CNN & RNN models, while 100% of the students were used for testing and validation purposes. The purpose of this dataset overlap is to estimate the blind and non-blind performance of the model for clinical use cases. Based on this evaluation process, the values of AFI were tabulated w.r.t. Number of Students (NS) in table 2 as follows,

NS	**AFI (%) BE SEM [3]**	**AFI (%) TeS LA [19]**	**AFI (%) FGW ANN [32]**	**AFI (%) PMS IE MDL**
390	68.15	64.43	69.78	90.44
585	68.46	64.85	70.16	90.91
780	68.71	65.23	70.49	91.37
975	68.92	65.76	70.88	91.87
1170	69.09	66.33	71.27	92.32
1565	69.19	66.82	71.58	92.73
1955	69.28	67.34	71.90	93.17
2345	69.40	67.89	72.26	93.65
2735	69.54	68.49	72.65	94.10
3125	69.67	68.95	72.96	94.49
3320	69.83	69.34	73.25	94.91
3905	70.01	69.84	73.61	95.37

4100	70.20	70.33	73.97	95.83
4295	70.38	70.82	74.32	96.28
4490	70.55	71.32	74.67	96.73
4690	70.73	71.82	75.03	97.19
4845	70.93	72.31	75.39	97.66
5000	71.12	72.81	75.75	98.11

Table 2. Accuracy of field inclination identification for different models under real-time use cases

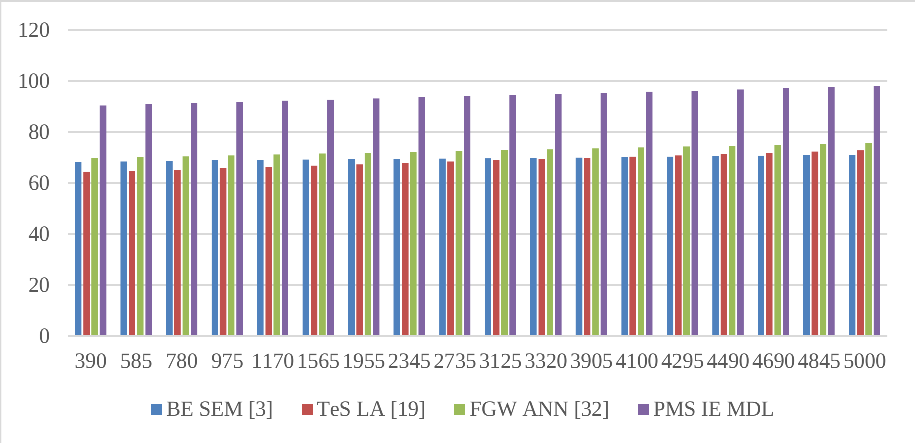

Figure 5. Accuracy of field inclination identification for different models under real-time use cases

Figure 5 shows that the proposed model is 16.3 percent better than BE SEM [3], 14.5 percent better than TeS LA [19], and 10.4 percent better than FGW ANN [32] for multiple types of comparisons. Using CNN for initial inclination estimation and RNN for final inclination classification has resulted in this improvement. Table 3 shows the results of the precision of inclination identification (PIA) study in the same way,

NS	PIA (%) BE SEM [3]	PIA (%) TeS LA [19]	PIA (%) FGW ANN [32]	PIA (%) PMS IE MDL
390	73.66	74.56	83.86	92.24
585	74.06	75.01	84.30	92.73
780	74.41	75.40	84.72	93.18
975	74.83	75.92	85.19	93.70
1170	75.23	76.45	85.63	94.19
1565	75.56	76.89	86.00	94.61
1955	75.90	77.36	86.40	95.04

2345	76.27	77.86	86.84	95.51
2735	76.68	78.41	87.28	96.01
3125	77.01	78.84	87.64	96.42
3320	77.32	79.22	88.01	96.82
3905	77.69	79.69	88.44	97.29
4100	78.07	80.16	88.87	97.76
4295	78.45	80.63	89.29	98.22
4490	78.82	81.10	89.71	98.62
4690	79.20	81.58	90.14	98.97
4845	79.58	82.06	90.57	99.27
5000	79.96	82.53	91.00	99.49

Table 3. Precision of field inclination identification for different models under real-time use cases

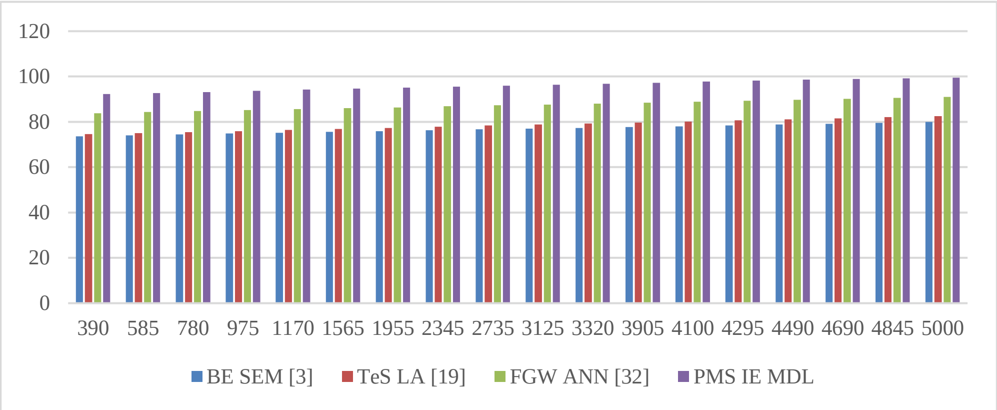

Figure 6. Precision of field inclination identification for different models under real-time use cases

Figure 6 shows that the proposed model's PIA performance is 18.5% better than that of BE SEM [3], 14.5% better than that of TeS LA [19], and 8.3% better than that of FGW ANN [32] based on this evaluations. For example, a field's inclination percentage can be accurately identified using CNN & RNN, resulting in better real-time performance. As can be seen in table 4, similar observations were made for the recall of field identification (RFI),

NS	RFI (%) BE SEM [3]	RFI (%) TeS LA [19]	RFI (%) FGW ANN [32]	RFI (%) PMS IE MDL
390	70.91	71.28	73.16	91.18
585	71.26	71.72	73.55	91.65
780	71.56	72.12	73.91	92.11

975	71.88	72.66	74.32	92.62
1170	72.16	73.22	74.71	93.09
1565	72.38	73.70	75.04	93.50
1955	72.59	74.20	75.39	93.94
2345	72.84	74.74	75.76	94.41
2735	73.11	75.33	76.16	94.89
3125	73.35	75.79	76.48	95.29
3320	73.58	76.19	76.79	95.69
3905	73.85	76.68	77.16	96.15
4100	74.14	77.18	77.54	96.62
4295	74.41	77.67	77.91	97.08
4490	74.69	78.17	78.28	97.53
4690	74.97	78.67	78.65	98.00
4845	75.26	79.17	79.03	98.47
5000	75.54	79.67	79.41	98.94

Table 4. Recall of field inclination identification for different models under real-time use cases

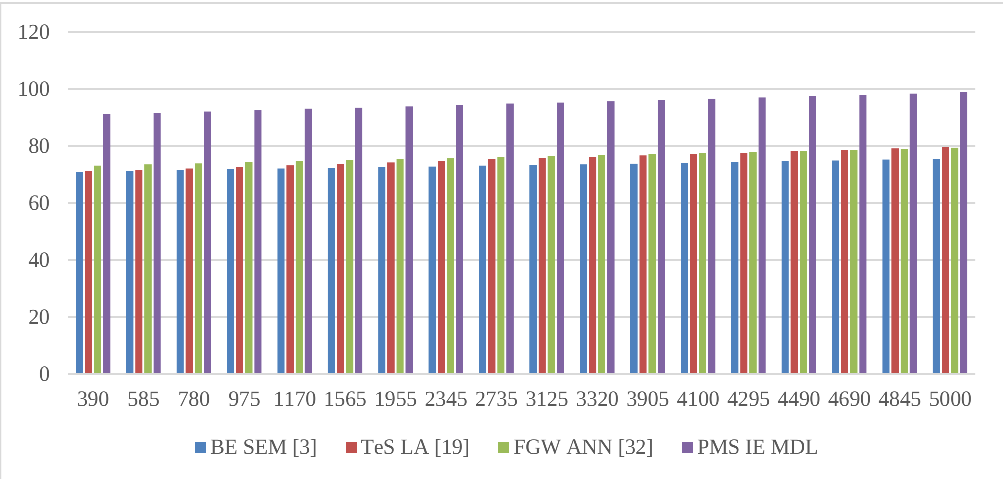

Figure 7. Recall of field inclination identification for different models under real-time use cases

Figure 7 shows that the proposed model is 14.8 percent better than BE SEM [3], 15.4 percent better than TeS LA [19], and 18.3 percent better than FGW ANN [32] for RFI performance under multiple evaluations. Thus, students' interests can be accurately predicted using a combination of behavioural and statistical parameters along with temporal analysis. Table 5 shows the findings for evaluation delay (DE), which can be seen as follows,

NS	DE (ms) BE SEM [3]	DE (ms) TeS LA [19]	DE (ms) FGW ANN [32]	DE (ms) PMS IE MDL
390	14.18	14.02	15.12	8.97
585	14.25	14.10	15.20	9.01
780	14.31	14.18	15.28	9.06
975	14.38	14.29	15.36	9.11
1170	14.43	14.40	15.44	9.16
1565	14.48	14.49	15.51	9.20
1955	14.52	14.59	15.58	9.24
2345	14.57	14.70	15.66	9.28
2735	14.63	14.81	15.74	9.33
3125	14.67	14.90	15.80	9.37
3320	14.72	14.98	15.87	9.41
3905	14.77	15.08	15.95	9.46
4100	14.83	15.18	16.03	9.50
4295	14.88	15.28	16.10	9.55
4490	14.94	15.37	16.18	9.59
4690	15.00	15.47	16.25	9.64
4845	15.05	15.57	16.33	9.68
5000	15.11	15.67	16.41	9.73

Table 5. Delay needed during field inclination identification for different models under real-time use cases

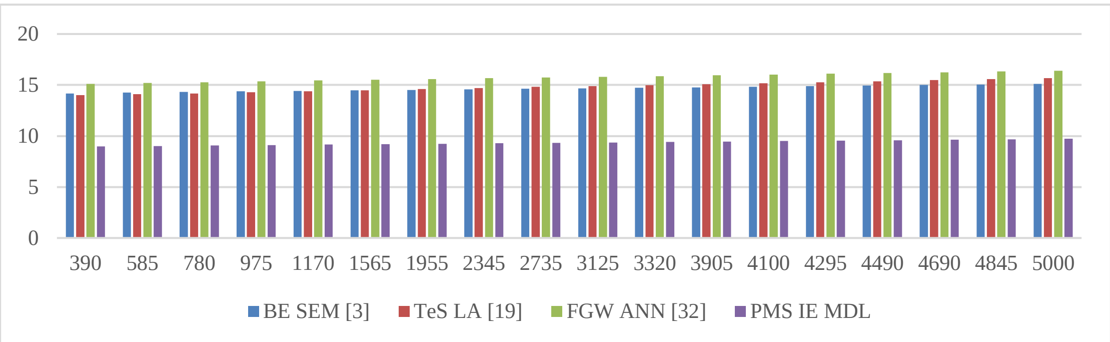

Figure 8. Delay needed during field inclination identification for different models under real-time use cases

The proposed model, when compared to BE SEM [3], TeS LA [19], and FGW ANN [32], performs 14.5% better than the original, 18.5% better than the second-best, and 15.2% better than the third-best models under variety of use cases. The use of a pre-trained CNN model and RNN helps reduce computational redundancy when evaluating inclination classes, which is why this improvement has been obtained for multiple use cases. Since the proposed model outperforms many existing models in terms of classification and inclination detection, it can be put to good use in a wide range of real-time application deployment scenarios.

V. CONCLUSION & FUTURE SCOPE

The proposed model is capable of improving accuracy of inclination classification for multiple users due to integration of high-density feature extraction & selection layers. These layers comprise of LSTM & GRU Models, and are used to support classification operations. These operations showcase further enhancements due to integration of psychological questionaries which assist in identification of instantaneous student behaviour & inclination levels. Due to which, the model is capable of achieving 16.3 percent better accuracy than BE SEM [3], 14.5 percent better than TeS LA [19], and 10.4 percent better than FGW ANN [32] for multiple types of comparisons. It also showcased 18.5% better precision than that of BE SEM [3], 14.5% better than that of TeS LA [19], and 8.3% better than that of FGW ANN [32] based on these evaluations. The model also showcased 14.8 percent better recall than BE SEM [3], 15.4 percent better than TeS LA [19], and 18.3 percent better than FGW ANN [32] for RFI performance under multiple evaluations. In terms of speed, when compared to BE SEM [3], TeS LA [19], and FGW ANN [32], performs 14.5% better than the original, 18.5% better than the second-best, and 15.2% better than the third-best models under variety of use cases. The use of a pre-trained CNN model and RNN helps reduce computational redundancy when evaluating inclination classes, which is why this improvement has been obtained for multiple use cases. Since the proposed model outperforms many existing models in terms of classification and inclination detection, it can be put to good use in a wide range of real-time application deployment scenarios. In future, the proposed model's performance can be improved via integration of multiple deep learning models including Generative Adversarial Networks (GANs), Q-Learning, and Auto encoders. It must also be validated on larger sets, and can be optimized via integration of multiple bioinspired models that can optimize accuracy and integrate large set of analysis parameters for clinical use cases.

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