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CONVERSATIONS TO CLASSIFICATION: LSTM AND LOGISTIC CLASSIFIERS FOR CATEGORIZING LEARNING STYLES THROUGH VERBAL DISCOURSE

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ABSTRACT:
This paper provides a guiding framework for discourse in pedagogical & andragogic classrooms composed of differentiated learning abilities. In this article, we investigate how verbal discourse can be modified to accommodate different modes of individual learning using Long Short-Term Memory (LSTM) classifiers. For centuries, verbal instructions have been at the heart of learning in various contexts, from ancient schools to integrated e-learning environments. By applying the VAK (Visual-Auditory-Kinesthetic) model, this study employs logistic classifiers and LSTM models to analyze a dataset of 15,450 data points of verbaldiscourse, achieving accuracies of 94.302% and 95.29%, respectively. It establishes that LSTM classifiers are highly effective at determining learning styles from verbal interactions. This approach discusses the integration of predictive classifier models to implement verbal instructional methodologies significantly conducive to teaching visual, auditory, and kinesthetic learners.

Keywords: Artificial Intelligence, Machine Learning, VAK Model, Logistic Classifiers, Differentiated Learning

INTRODUCTION: :

A learning style refers to an individual's preferred method or approach to acquiring and processing new ideas, concepts, techniques, and information. Understanding one's learning style helps an educator customize teaching-learning material to be more effective and engaging. Among various avant-garde educational methods emerging, verbal discourse has remained a fundamental and nearly irreplaceable approach to instruction since the inception of educational institutions before BCE. Temple Schools (Ancient Egypt), Edubbas (Mesotopamia), Gurukuls(Ancient India), Confucian Academies (Ancient China), and Gymnasiums (Ancient Greece) were set up to train priests, administrators, philosophers, government officials, and physical training, well before the advent of Christ in the Gregorian Calendar. While the aims and curriculum of their education differed, the method of instruction was primarily, and irrefutably, verbal and written instruction. Revising and transforming learning materials to meet the needs of learners with diverse learning styles begins with modifying our verbal discourse. In this paper, we propose a new framework to detect students' learning styles based on verbal methods of instruction. The questions that form the grounds for investigation in this paper are:

1. Which semantic structures are recurrent in individuallearning styles of the VAK models?
2. What methodologies can teachers devise to deliver oral modules that cater to VAK learning styles?

VAK(VISUAL-AUDITORY-KINESTHETIC)MODEL: :

Huda (2014), as cited in Wulansari (2016), emphasized that the VAK learning model is a multisensory learning model that engages and customizes teaching methods for three learning styles - Visual, Auditory, and Kinesthetic learners. Multiple studies indicate that students perform better in certain subjects when instructional methods adapt to their specific learning styles. However, Hussain (2017) suggested fusing diverse teaching styles and strategies rather than concentrating on a particular teaching technique.

Brown stated that learning styles are a natural congruence of cognitive and psychological aspects of the mind. Students' performance was affected in terms of how they perceive, interact, and respond to the learning environment - highlighting the importance of adhering to the psychological needs of advanced and general learners. VAK is one of the many learning models coined - some others include David Kolb's model, Peter Honey and Alan Mumford's model, Anthony Gregorc's model, Felder-Silverman's learning style, Gardner's theory of multiple intelligence, and so on (Pashler et al., 2008).The selection ofVAK learning model is favored by its avoidable need for complex computation when identifying types of learners.

Personalized computing has existed for a couple of decades, prompting all modern systems to have a touch of personalization. The development of e-learning systems has undergone significant advancements, transitioning from basic computerized instruction, such as quizzes, to adaptive virtual environments (Wild et al., 2014) that offer digital resources seamlessly. A differentiated classroom creates and provides learning opportunities for advanced, average, and slower learners by considering their learning styles—whether visual, auditory, or kinesthetic. Since accessible AI-powered chatbots, AI tools have taken a front seat to aid teachers in planning teaching-learning materials delivered in a digital medium of instruction.

Despite automating classroom activities through machine learning, AI excels in tasks like grading essays rather than creating meaningful learning experiences. This limitation is due to the lack of integrated sensor technologies, comprehensive research frameworks, and widespread access to advanced tools in educational settings. (Lamb et al., 2023) In developing countries, where inequitable access to technological advancement favors economically privileged classes, teachers refrain from assigning digital coursework to students. However, integrating AI into verbal discourse allows teachers to use AI to create a differentiated learning classroom without the need for the digital involvement of students (without resources).

METHODOLOGY:

Dataset: The dataset used for building the model was exported from an open source (www.kaggle.com/datasets/zeyhadkhalid/learning-style-vak), sized at 15450 * 2 (15450 rows, 2 columns). The columns are segregated into sentences and types of learners. Types of learners are further classified into 3 nominal data types - Visual, Kinesthetic and Auditory. The corresponding sentences are verbal statements that cater to the needs of these learners. The dataset was analyzed in Python 3.0 on a Jupyter Notebook.

Sentence		Type	
English sentence		Learning style	
Show More Sente...	4%	Visual	38%
The idea of combi...	0%	Kinesthetic	31%
Other (14780)	96%	Other (4804)	31%

	Type	Sentence
0	Auditory	Ali, who was two at the time, loved the story ...
1	Kinesthetic	Tubercle bacilli can remain dormant for years ...
2	Visual	Speck disagreed with my assessment of the drea...

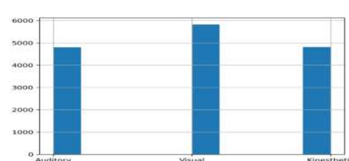

Fig 1. Visual summary(bar graph) of the dataset

LOGISTIC CLASSIFIERS :

Logistic regression, despite its name, is a classification technique rather than a forecasting regression model. It models the probability that a given input belongs to a particular class. Such probability ranges between 0 to 1, and is defined by the equation

$$P(y = 1|X) = \frac{1}{1 + e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+.....+\beta_n x_n)}}$$

Here, P(y=1|X) represents the probability that the dependent variable y belongs to class 1, given the feature X.

$$Predicted\ class = \begin{cases} 1\ if\ P(y = 1|X) \geq 0 \\ 0\ if\ P(y = 1|X) \leq 0 \end{cases}$$

The decision rule in binary classification as the one mentioned above, involves selecting a threshold (usually around 0.5). However, the threshold can be modified based on the user's expertise or the cost of false positives and false negatives.

In VAK dataset, a large percentage of the work involves pre-processing data – eliminating punctuation from sentences, encoding and decoding, cleaning them before vectorization, and using CountVectorizer() to identify frequent words. Once the data is processed, LogisticRegression() model is deployed, to create a classifier that categorizes your sentences into three types - based on how they would appeal most to Kinesthetic, Auditory and Visual learners.

LONG SHORT-TERM MEMORY (LSTM): DEEP RECURRENT NEURAL NETWORKS (RNN):

LSTM is a variant of recurrent neural network(RNN) architecture which identifies long term dependencies in sequential data. Recurrent Neural Networks (RNNs) are specifically aimed at time-dependent data processing(such as time series analysis) by utilizing hidden units carrying information from earlier time steps/frames. Traditional RNNs lacked the ability to learn long term relationships due to exploding gradients or vanishing. Hochreiter and Schmidhuber (1997) proposed LSTM networks that overcame the problems faced in traditional RNN's, due to their advanced structure, which consist of memory cells and gating mechanisms.

ARCHITECTURE: :

LSTM networks' memory cell is the main component that can retain information for a long period of time. The LSTM architecture contains the following major parts:

i. Memory Cell: The memory cell's role is to keep its cell state for a long time. It works like a conveyor belt in terms of transporting information across the network.

ii. Gates: Three types of gates are used to manage the way data flows into and out of LSTM memory neural networks' memory cells:

a. ***Forget Gate***: this is responsible for the cell state to decide what data should be thrown away from it. The previous hidden state and concatenated input are used as arguments by a sigmoid function then used on it.

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f)$$

W_f are the weights, b_f is the bias, h_{t-1} is the previous hidden state and x_t is the current input

b. Input Gate: this regulates new information addition on cell state which interacts with candidate values' generation through tanh activation function besides gating using function sigmoid

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i)$$

$$C_t = tanh(W_C * [h_{t-1}, x_t] + b_C)$$

C_t is the candidate cell state, W_i and W_c are the weights, b_i and b_c are the bias

c. Output Gate: responsible for controlling information that leaves cell state to arrive next layer

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using the output state activation concerning which parts should go out of it in terms of sigmoid function

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t tanh(C_t)$$

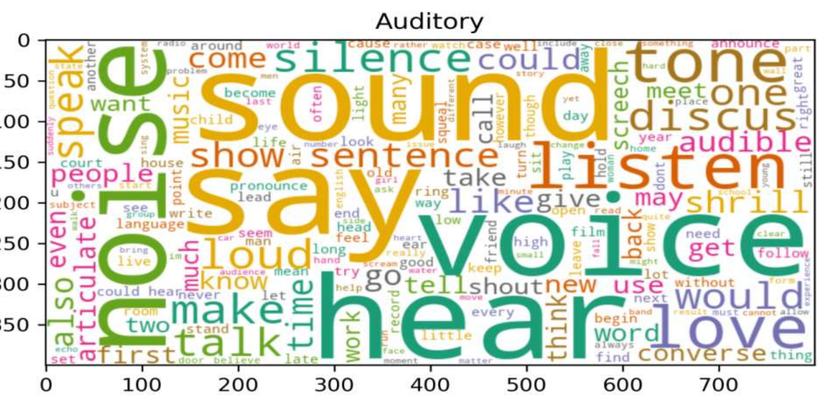
h_t *is the hidden state output*

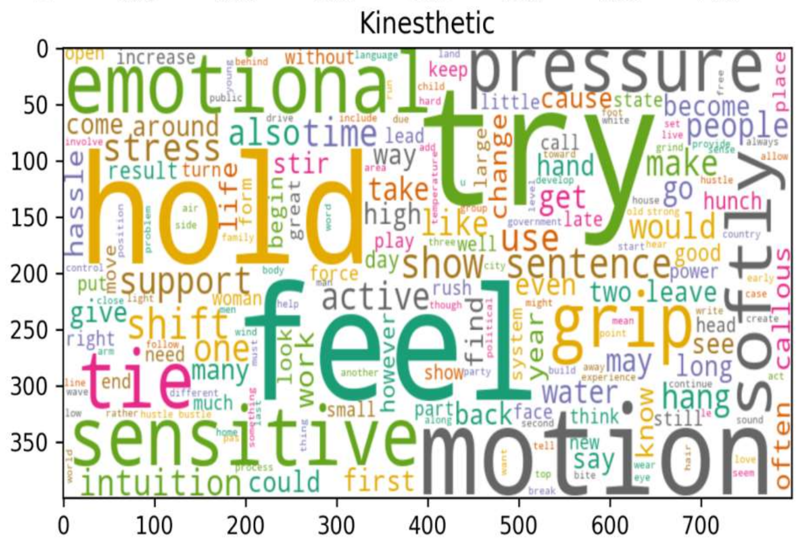
(Note: In the equations above, * denotes multiplication)

Like logistic classifiers, LSTM requires preprocessing of data, i.e., encoding, tokenization, and word vectorization. Once the data is processed, a GloVe package of 6 Billion words and 200 dimensions(glove.6B.200d.txt) embeds GloVe and reads the word vectors.

ANALYSIS :

Visualization: Word clouds were generated in Jupyter Notebook using the wordcloud package, succeeding the cleaning and vectorization of the dataset. This visualization technique was utilized to identify the most frequently-used words among students with different learning styles. For instance, “sound, silence, tone, hear, love, converse, word” are quite popular with auditory learners. Kinesthetic learners lean towards words that have a sense of tangibility - “feel, tie, emotional, grip, softly, pressure”. Visual learners respond best to statements that leverage their eyesight and visually imaginary senses - “idea, see, vision, focus, picture, illustrate”





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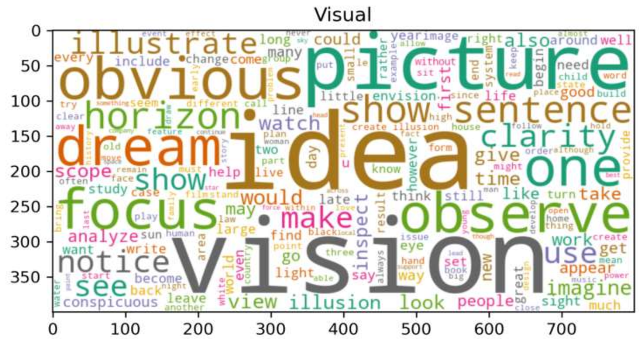

Fig 2,3,4. Word Clouds for vocabulary that appeals most to visual, auditory and kinesthetic learners

LOGISTIC CLASSIFIERS:

Logistic Classifier is, by far, the best binary classifier for datasets that can be encoded and decoded (i.e., ordinal and nominal datasets). After an 80-20 training-test split, train data is fit using the LogisticRegression() model. When the test data is evaluated against the model, it returns 94.3042% accuracy. High accuracy was attainable, due to the model not being over/under fit, because of inappropriate processing methods or low/high train/test splits.

```
# Bulding the model and applying it to the encoded data
classifier = LogisticRegression()
classifier.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression()
```

```
#evaluationg model score
score = classifier.score(X_test, y_test) * 100
print("Model score = " + str(score))
```

```
Model score = 94.30420711974111
```

Fig 5. Accuracy metrics of the logistic regression model

To gauge the model, 3 experimental statements were provided to the model. It was asked to classify what type of learners would resonate with the sample sentences. The results are given below. **EVALUATION**:

```
# Initialize data
sentence1 = "I want to see the mountains and feel the sea against my skin again"
sentence2 = "All we need to do is visualize how these lines intersect"
sentence3 = "I hear the wind call my name, the sound that leads me home again"
```

```
Kinesthetic
Visual
Auditory
```

Fig 6. Sentences classified with the Regression Model.

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LSTM ARCHITECTURE :

A summary of the input, output and hidden layers which are built into the LSTM model are outlined below. The shape of the output layer is mentioned beside each layer.

Layer (type)	Output Shape	Param #
embedding_18 (Embedding)	(None, 48, 200)	5,355,600
lstm_32 (LSTM)	(None, 48, 256)	467,968
lstm_33 (LSTM)	(None, 128)	197,120
dense_16 (Dense)	(None, 3)	387

```
Total params: 6,021,075 (22.97 MB)
Trainable params: 665,475 (2.54 MB)
Non-trainable params: 5,355,600 (20.43 MB)
```

Fig 7. Layers of Long Short Term Memory RNN

Data provided to LSTM is split into 80% training and 20% test data. The model is instructed to run 10 simulations (epochs), at the end of which, accuracy rockets from 57.39% accuracy to 95.29% accuracy.

```
history = model.fit(X_train,
                    y_train,
                    validation_data=(X_test, y_test),
                    verbose=1,
                    batch_size=64,
                    epochs=10)
```

```
model.evaluate(X_test, y_test, verbose=1)
```

```
97/97 ━━━━━━━━━━━━━━━━━━━━ 5s 46ms/step - accuracy: 0.9504 - loss: 0.0989
[0.09718240797519684, 0.9533980488777161]
```

Fig 8. Accuracy metrics of VAK-LSTM

A comparison of accuracy between training and validation, and of loss between training and validation is visualized below. Loss and validation share an inversely proportional relationship for this model. he loss in datasets neared 0, while the accuracy soared above 95%.

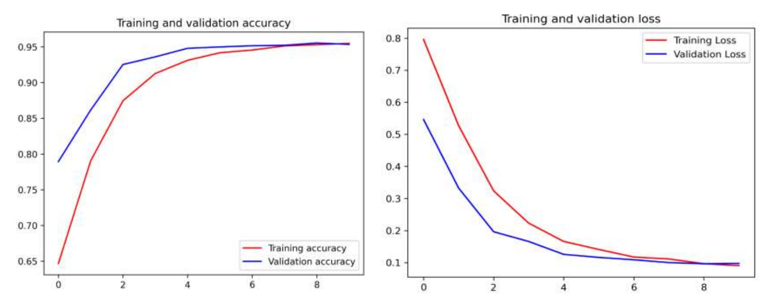

Fig 9. Comparison of training and validation scores in accuracy improvement & loss of the VAK-LSTM

To assess the effectiveness of the LSTM, 3 sample sentences were fed into the neural network.

```
sentences = ["Would you all like to make written notes or work on your tablets?",
             "Can you hear the noise?",
             "Today, we're going a fieldtrip to see how employees use business analytics everyday!"
            ]
```

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The model returns "Visual", "Auditory" and "Visual" to the sentences mentioned in the test. The classified sentences provide >89% accuracy, with 99% being the highest.

```
Would you all like to make written notes or work on your tablets?
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step
Visual : 0.8976365327835083


Can you hear the noise?
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step
Auditory : 0.9997965693473816


Today, we're going a fieldtrip to see how employees use business analytics everyday!
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
Visual : 0.9861197471618652
```

Fig 10. Accuracy metrics of samples provided to the VAK-LSTM

DISCUSSION :

In differentiated classrooms, understanding and leveraging student engagement patterns through verbal discourse becomes key to effective teaching. Long Short-Term Memory (LSTM) classifiers offer a sophisticated approach to analyzing these engagement patterns. They are adept and can capture temporal dependencies within student interactions. This capability is particularly valuable in educational settings where the dynamics of verbal discourse—comprising both audio and textual elements—play a significant role in learning processes. LSTM classifiers can be employed to process and analyze data from diverse sources such as classroom discussions, verbal responses, and interaction logs. By examining these data streams, LSTMs can identify patterns indicative of different learning styles—auditory, visual, and kinesthetic. Studies such as those by Hsu et al. (2020) have highlighted the efficacy of LSTM models in educational contexts, noting their ability to provide granular insights into learner behavior and preferences.

However, the LSTM model works only in schools where the teachers are trained and equipped to handle AI-Integrated tools. The availability of such tools, despite the teacher being trained, in school premises poses a problem too.

The lack of digital infrastructure and trained personnel to operate AI models is one of the biggest challenges India faces in the Education industry. With the rise of data sciences and artificial intelligence in a span of 3 years, technological resources in classrooms are inadequate, limited and suboptimal(in terms of availability and performance) in overpopulated countries like India. To bridge the gap between underhanded resources and advance tech, the VAK-LSTM model could provide a semi-structured solution to improve teaching methodologies, especially for children with learning disabilities. However, the model is limited to English (as of 2024), and fails when oriental/regional Indian languages are supplied to it. The availability of VAK-LSTM model in regional languages would be a game-changer for students whose medium of instruction is their oriental language. Another addition to this model could be integration of a speech-to-text feature with the VAK LSTM classifier, coupled with a user-friendly interfacewould provide easy access to teachers who are not acquainted with data science or computer literacy to use the model in regular discourse.

CONCLUSION :

By incorporating these insights, educators can personalize verbal discourse and oral communication to align with the identified learning styles, thereby optimizing instructional strategies. This customized

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approach, not only enhances individual learning experiences but also inculcates a more inclusive classroom environment. To conclude, leveraging LSTM classifiers to analyze and adapt teaching methodologies ensures that instructional methods are responsive to the diverse needs of students, thereby supporting more effective and equitable learning outcomes.

REFERENCES :

Faryadi, Q. (2017). Effective Teaching and Effective Learning: Instructional Design perspective. *Independentresearcher*. https://www.academia.edu/32441472/Effective_Teaching_and_Effective_Learning_Instructional_Design_Perspective

Horning, A. S., & Brown, H. D. (1981). Principles of language learning and teaching. Modern Language Journal, 65(4), 417. https://doi.org/10.2307/327392

Hochreiter, S., &Schmidhuber, J. (1997). Long Short-Term memory. *Neural Computation*, *9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Hussain, I. (2017b). Pedagogical Implications of VARK Model of Learning. Journal of Literature, Languages and Linguistics, 38, 33–37. https://iiste.org/Journals/index.php/JLLL/article/download/39354/40464

Lamb, R., Choi, I., & Owens, T. (2023a). Artificial Intelligence and Sensor Technologies the Future of Education Students with and without Intellectual and Developmental Disabilities. International Journal of Psychology and Neuroscience, 9(1), 30–36. https://doi.org/10.56769/ijpn09102

Nazempour, R., &Darabi, H. (2023). Personalized Learning in Virtual Learning Environments Using Students' Behavior Analysis. Education Sciences, 13(5), 457. https://doi.org/10.3390/educsci13050457

Pashler, H., McDaniel, M., Rohrer, D., & Bjork, R. (2008). Learning Styles. Psychological Science in the Public Interest, 9(3), 105–119. https://doi.org/10.1111/j.1539-6053.2009.01038.x

Ramadian, O. D., Cahyono, B. Y., &Suryati, N. (2020a). The Implementation of Visual, Auditory, Kinesthetic (VAK) Learning Model in Improving Students' Achievement in Writing Descriptive Texts. English Language Teaching Educational Journal, 2(3), 142. https://doi.org/10.12928/eltej.v2i3.946

Ramadian, O. D., Cahyono, B. Y., &Suryati, N. (2020a). The Implementation of Visual, Auditory, Kinesthetic (VAK) Learning Model in Improving Students' Achievement in Writing Descriptive Texts. English Language Teaching Educational Journal, 2(3), 142. https://doi.org/10.12928/eltej.v2i3.946

Wulansari, Y. (2016) The use of visual auditory kinesthetic (VAK) learning model to improve students' reading comprehension (Unpublished Thesis). Department of Teacher Training and Education Faculty State Institute for Islamic Studies (IAIN) Salatiga