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AUTOMATED ENHANCED LEARNING SYSTEM FOR SLOW LEARNERS

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Abstract: This research proposes a novel approach to enhance the learning experience for slow learners by detecting their learning styles using fingerprint recognition technology. The proposed system integrates machine learning algorithms to analyze and classify learning styles based on the VAK (Visual, Auditory, Kinesthetic) model. By recognizing individual learning styles, the system aims to personalize educational strategies and resources to better suit the preferences and cognitive strengths of learners. This approach has the potential to optimize the learning experience for slow learners and improve their academic performance. The proposed system is expected to contribute to the development of personalized learning system that can cater to the diverse needs of learners.

***Keywords* – Fingerprint, Learning Style, Convolutional Neural Network.**

I. INTRODUCTION

In the realm of education, every student possesses unique abilities, challenges, and learning styles. However, a subset of students, often referred to as low learners, face additional hurdles in their educational journey. The term "low learners" encompasses individuals who may experience difficulties in grasping academic concepts at the pace or depth expected for their age or grade level. These challenges can manifest across various subjects and domains, impacting both academic performance and self-esteem. Traditional educational approaches, which often prioritize standardized assessments and uniform teaching methods, may inadvertently exacerbate these challenges by failing to accommodate the diverse needs of low learners.

Every person has their own learning style. If the faculty teaches students according to their learning style and measures their performance accordingly, the academic performance of students increases. There are different ways to define the learning style of a student. One way to define a learning style is through fingerprints. Fingerprints are very crucial and unique for every person. They start forming in the 12th week of fetal development. The pattern of fingerprints is established completely by the 19th week and remains unchanged throughout life. There is a correlation between the brain and fingerprints, from which we can define the type of learning style.

There are three major types of fingerprints: loop, whorl, and arch. The loop has a ridged pattern that starts on one side of the finger, curves around, and ends on the same side. The whole has a spiral pattern of ridges that surrounds a central point. The arch has a ridged pattern that starts on one side, rises in the middle and then falls on the other side.

Fig 1: Type of Fingerprint

VAK (Visual, Auditory, and Kinesthetic) is used for detecting learning style. Visual learners like to read; they usually memorize things by seeing pictures or graphics; they observe rather than act or talk; they remember the face of a person, and they generally perform well in written exams. Auditory learners enjoy talking; they memorize things by listening or by speaking loudly; they enjoy music, and they generally perform well in oral exams. Kinesthetic learners like a 'hands-on' approach and physical activity; they generally perform well in practical exams. People do not have one prominent learning characteristic; they might have more than one learning characteristic.

The objective of this paper is to develop a system that accurately detects and classifies the learning of slow learners through fingerprint analysis. By doing so, we aim to pave the way for an enhanced learning experience that caters to the individual needs and performance of each student.

II. RELATED WORK

Supriyadi et al. [2] discussed about learning style and potential intelligence of learner through dermatoglyphics analysis. Learners have the potential intelligence: visual-spatial, logical-mathematical, naturalist, interpersonal; the learning styles: visual, kinesthetic, and audio. The Authors have highlighted the correlation of brain and fingerprint. The thumb is connected on the area of the lobe of the pre-frontal; Index finger connected on area of frontal lobe; middle finger with parietal lobe; ring finger associated with temporal lobe and little finger with occipital lobe.

Arianda et al. [3] proposed a system to detect the personality of student through fingerprint. The Author used the gray co-occence matrix (GLCM) for feature extraction and Random forest and Maximum Entropy method for classification. The Author took a database of 123 students and took fingerprint of middle, ring and little finger with ink. From fingerprint he found out the childern’s learning style and personality. System gives accuracy of 95% for random forest method and 44% for maximum entropy method.

Nidhi Desai et al. [4] described correlation between fingerprint pattern and human behavior. The left hemisphere of brain manages the logical computational capabilities and responds to academic expression whereas right hemisphere of brain controls the aspects of human life related to emotion, passion, creation, intuition. The brain has frontal lobe, parietal lobe, temporal lobe and occipital lobe. Frontal lobe works for thinking and imagination and it associated with index finger; parietal lobe works for kinesthetic function and is associated with middle finger; Occipital lobe works for visual processing and is associated with little finger; temporal lobe works for sound/speech processing and is associated with ring finger; pre-frontal lobe with executive and cognitive function and is associated with thumb.

Amit Sexsena et al. [10] proposed an IOT based system which will automatically categorize students, keep the record of their performance, assignment, submission history etc. This will help in reducing the manpower of faculty members and enhance the performance of students from 5 to 42% by custom designing activities as per the innate learning style.

Hoang Tieu Binh et al [12] used an artificial neural network to predict academic performance based on students’ learning style. Author concretely described an approach on multilayer perceptron to predict academic result based on learning styles.

III. METHODOLOGY

I gave a questionnaire to define learning style to 100 students of different age group and asked these students to solved it. And fingerprints of this student were also taken. From that questionnaire I figured out their learning style and matched that data with the fingerprint data.

3.1 Learning style Assessment:

To assess the learning styles of participants, we designed a comprehensive questionnaire incorporating established frameworks of the VAK model (Visual, Auditory, Kinesthetic). The questionnaire consisted of a series of statements or scenarios related to various learning modalities, and participants were asked to indicate their level of agreement or preference for each item. The responses were then scored and analyzed to determine the dominant learning styles of each participant.

3.2 Fingperint Data Collection:

Fingerprint data were collected using a Mantra MFS100 Biometric Fingerprint Scanner. Prior to data collection, participants were briefed on the purpose of the study and provided informed consent for the use of their biometric data. Research utilized a custom-built localhost site designed to capture fingerprint data from participants. Participates were guided through the fingerprint data capture process step by step. The participants asked to place their finger on the scanner and provided real-time feedback to ensure that the fingerprint was captured successfully. Special care was taken to ensure the privacy and confidentiality of participants' personal information, and all data were securely stored and anonymized for analysis.

3.3 CNN Classification:

For fingerprint data, we utilized the NIST Special Database 4, which contains a comprehensive collection of 8-bit gray scale images of fingerprint image groups (FIGS). This dataset, curated by the National Institute of Standards and Technology (NIST), which contains 4000 fingerprint images in PNG format. Steps for CNN Classification:

1. Input Layer: The input layer receives images of size 128x128 pixels.
2. Convolutional Layer: The architecture includes multiple convolutional layers:
   Convolutional layer 1: 32 filters with a kernel size of (3, 3), followed by ReLU activation.
   Convolutional layer 2: 32 filters with a kernel size of (3, 3), followed by ReLU activation.
   Convolutional layer 3: 64 filters with a kernel size of (3, 3), followed by ReLU activation.
   Convolutional layer 4: 64 filters with a kernel size of (3, 3), followed by ReLU activation.
   Convolutional layer 5: 64 filters with a kernel size of (3, 3), followed by ReLU activation.
   Convolutional layer 6: 128 filters with a kernel size of (3, 3), followed by ReLU activation.
3. Max Pooling Layer: Max pooling is used to downsample feature maps and reduce spatial dimensions, helping to capture the most important features while reducing computational complexity. Each max pooling layer has a pool size of (2, 2).
4. Flatten Layer: After the last convolutional layer, the feature maps are flattened into a one-dimensional vector.
5. Fully Connected (Densed) Layer: The flattened feature vector is passed through fully connected dense layers. There is a dropout layer with a dropout rate of 0.5 to prevent overfitting.
6. Output Layer: Output Layer consists of neuron which is equal to the type of classification. For fingerprint classification output layer consists of 5 neuron for five class(Arch, whorl, Left Loop, Right Loop and tented Arch) whereas for learning style classification there are three neurons which is for Visual Learning Style, Auditory Learning Style, Kinesthetic Learning Style.

IV. EXPERIMENTAL RESULTS

Table 1 shows the Result which we got from questionnaire and fingerprint data which were taken from sensor

Sr No	Name	Gender	Age	Learning Style from Questionnaire in %			Type of Fingerprint on following fingers		
				Visual	Auditory	Kinesthetic	Little	Ring	Middle
1	Dax Panchal	Male	16	40	20	40	Loop	Loop	Whorl
2	Yash Gharat	Male	23	25	35	40	Whorl	Whorl	Whorl
3	Anupama Desai	Female	34	70	25	5	Loop	Loop	Loop
4	Rupali Tirale	Female	28	40	35	25	Loop	Loop	Loop
5	Kailash Tupe	Male	37	50	40	10	Loop	Whorl	Whorl
6	Neha Pagaria	Female	30	40	30	30	Loop	Whorl	Loop
7	Sandesh Gurav	Male	34	50	25	25	Loop	Loop	Loop
8	Sanket Shinde	Male	23	35	35	30	Loop	Arch	Arch
9	Rushikesh Pawar	Male	25	25	50	25	Loop	Whorl	Arch
10	Pawankumar Satish Mandhare	Male	24	50	30	20	Loop	Loop	Loop
11	Atish Phanse	Male	26	40	40	20	Loop	Whorl	Loop
12	Laxmikant Bhogal	Male	33	50	35	15	Loop	Whorl	Loop
13	Shubham Pujari	Male	16	20	30	50	Loop	Arch	Arch
14	Neha Gharat	Female	28	40	30	30	Loop	Whorl	Loop
15	Pratik Mandhare	Male	25	40	35	25	Arch	Loop	Arch
16	Vedant Deshmukh	Male	14	25	30	45	Whorl	Whorl	Loop
17	Harshad Kolekar	Male	14	15	35	50	Loop	Loop	Arch
18	Roshani Gorivale	Female	13	40	45	15	Whorl	Whorl	Whorl
19	Harshada Kadam	Female	13	35	35	30	Loop	Loop	Arch
20	Saee Shinde	Female	13	40	35	25	Loop	Whorl	Loop
21	Anita khunikor	Female	16	20	50	30	Loop	Arch	Arch
22	Kadam Sharman Samarpal	Male	19	50	10	40	Loop	Whorl	Loop

Table 1: Student Learning style and Their Fingerprint Data

The table shows the relation between fingerprints and learning styles, suggesting that specific fingerprint patterns may be associated with certain learning styles. According to the data, students with a loop structure on their little finger may have a visual learning style, while those with a whorl fingerprint on their ring finger may have an auditory learning style. Additionally, students with an arch pattern on their middle finger may have a kinesthetic learning style. The accuracy of CNN Classification is 83.34%.

V. CONCLUSION

The research paper presents a novel approach to enhancing the learning system for slow learners by utilizing fingerprint analysis to detect their unique learning styles, employing a CNN classifier for accurate classification. This system has potential to personalize learning experience, increase learning ability and improve engagement for slow learners.

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