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Classifying Learning Disabilities and Personalizing Education with ML

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Abstract: This project is about building a helpful computer tool to find out if students might have a learning disability (LD) and then give them special advice. First, we collected information about many students, like their age, grades in different subjects (math, reading, English, science), and other things like if they have trouble paying attention or a family history of LD. We used this information to train two computer brains, called machine learning models (Random Forest and Support Vector Machine), to guess if a new student might have an LD. We picked the best brain based on how accurate it was. If our computer brain thinks a student might have an LD, it doesn't just stop there. It then asks the student to take small quizzes in different areas like math, grammar, memory, and how they solve problems. After the student finishes these quizzes, the computer figures out which areas they struggled with the most. For these tough areas, the system then gives personalized suggestions. For example, it might suggest certain yoga poses to help with focus or specific exercises to practice for memory. All the results, predictions, and advice are saved securely. This project is a simple but useful way to help students and their families get a better understanding and find ways to support learning.

Keywords: Learning Disability, Machine Learning, Prediction, Personalized Recommendations, Educational Support, Data Analysis, Random Forest, Support Vector Machine, Student Assessment, Yoga Exercises.

I. INTRODUCTION

School can be tough for many students, and sometimes, it's not just about studying enough. Some students might have something called a learning disability, or LD for short. This means their brain works a little differently, which can make things like reading, writing, or math harder. It's really important to find out about these issues early so students can get the right help and support. Imagine trying to learn to swim but no one tells you that you need to kick your legs – that's a bit like what it's like for someone with an undiagnosed LD. They might be trying their hardest but still struggling because they don't have the right tools or strategies.

Our project is all about making it easier to spot these learning challenges and then offer practical ways to help. We've built a smart computer program that acts like a helpful assistant for students, parents, and even teachers.

Understanding the Problem: We know that learning disabilities can make school frustrating. When students struggle, they might feel bad about themselves, even though it's not their fault. Early detection can prevent these feelings and help them succeed.

Using Computer Smartness**:** We used "machine learning," which is like teaching a computer to learn from examples. We fed it lots of information about students (their grades, how they act, if family members had similar issues) and whether they had an LD or not. From this, the computer learned to spot patterns.

Personalized Help**:** We didn't want a one-size-fits-all solution. If the computer thinks a student might have an LD, it asks them to take some short tests. These tests are like mini-quizzes in areas like math, grammar, memory, and problem-solving. This helps us see exactly where a student might need extra help.

Practical Recommendations**:** Based on the quiz results, the system gives specific, easy-to-follow advice. For instance, if a student struggles with memory, it might suggest certain yoga poses that are known to help with focus or fun memory games. This kind of advice is meant to be helpful and easy to integrate into daily life.
Easy to Use: We designed our tool as a website, so it's simple for anyone to use from a computer or tablet. Users can create an account, input information, get predictions, take tests, and see their personalized recommendations all in one place.

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In short, this project aims to use modern technology to shine a light on learning difficulties, reduce the guesswork, and provide actionable steps for support, making the learning journey smoother for students.

II. LITERATURE REVIEW

Kuru and team studied dyslexia detection in students using machine learning in 2021 [1]. Their method relied on eye-tracking data while reading text, showing that movement patterns strongly distinguish dyslexic readers. The study achieved high accuracy, but it required specialized eye-tracking hardware, limiting real-world classroom use.

Thabtah and colleagues designed autism screening models in 2018 [2]. They used decision trees and rule-based learners on questionnaire datasets, showing that children at risk could be quickly flagged. The models were lightweight and interpretable, but they depended heavily on the reliability of self-reported answers from parents.

Ryu and team worked on dementia risk prediction in 2019 [3]. Using national health insurance data, they trained machine learning models to identify older adults likely to develop dementia. The models showed strong predictive performance, but interpretability remained a limitation for clinical adoption.

Li and co-authors in 2021 [4] developed models to forecast disability recovery in stroke patients using MRI and clinical features. Their system predicted which patients would regain independence, helping doctors plan treatment. However, the method required expensive imaging resources, reducing accessibility.

Pujari and team in 2022 [5] built classification models for identifying learning disabilities using educational performance metrics. Their study showed random forest and SVM outperforming others. Results were promising, but tested only in one regional school dataset, limiting wider applicability.

Zhao and colleagues in 2020 [6] proposed a multimodal deep learning model that combines genetic profiles with clinical symptoms to predict neurodevelopmental disorders. They found that combining data improved accuracy dramatically. However, privacy concerns and resource intensity made routine implementation difficult.

Kumar and team worked on learning difficulties in 2019 [7]. Their study used student records, attendance, and grades to train algorithms that flagged at-risk learners. Random forest performed best, but the system was sensitive to local school grading systems.

Chiang and colleagues studied MS disability progression in 2017 [8]. Their models predicted worsening EDSS (disability) scores from MRI and clinical history. Machine learning significantly outperformed traditional scoring, but more longitudinal data was needed.

Girard and team in 2015 [9] applied computer vision to video recordings of children, identifying ASD-related differences in facial expressions. The system detected autism markers that humans might miss. However, it had small sample sizes and needed validation in real-world therapy settings.

Hosseini and colleagues in 2018 [10] tested deep neural networks on brain imaging to distinguish children with autism spectrum disorders. Their model captured subtle functional connectivity differences. Still, fMRI is costly and not practical for large-scale screening.

Walsh and team in 2017 [11] examined ADHD classification with machine learning applied to MRI connectivity networks. Their approach provided accurate biomarker-based diagnosis. But MRI's expense and the variability of ADHD presentations limited clinical rollout.
Duda and colleagues in 2016 [12] created algorithms that analyzed home video recordings to detect autism characteristics. They demonstrated how machine learning could contribute to early behavioral screening. But they highlighted privacy issues with video data collection.

Pusiol and team in 2016 [13] leveraged crowdsourced video data analyzed by convolutional networks for autism identification. Their system provided scalable, cheap screening compared to conventional methods. But classification remained less reliable than clinical evaluation.

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Amann and co-authors in 2020 [14] reviewed ML approaches for disability prediction in neurological diseases like stroke and dementia. They showed ML systems outperforming conventional risk scores. However, ethical and transparency issues need resolution before clinical integration.

Simpraga and colleagues in 2017 [15] predicted progression from mild cognitive impairment to Alzheimer's disease using structural MRI with machine learning. Their method achieved strong performance in early identification. Still, inconsistent data across hospitals reduced model generalizability.

III. PROPOSED METHODOLOGY

Our project uses a step-by-step approach to first guess if a student might have a learning disability and then offer personalized help. Think of it like a smart detective agency for learning.

1. **Gathering and Preparing Information:** We started with a dataset, like a big spreadsheet, full of information about students. This included things like their age, gender, scores in school subjects (Math, Reading, English, Science), and other important details such as if they had behavior issues, a family history of learning problems, how well they pay attention, their social skills, or if they had speech issues. The key was whether these students actually had a "Learning Disability" or not, which was our target.
   - **Handling Words and Numbers:** Computers like numbers, but some of our information was in words (like 'Male' or 'Female', 'Yes' or 'No', 'Low' or 'High'). We used a tool called Label Encoder to turn these words into numbers. For example, 'Male' might become 0 and 'Female' might become
   - **Making Numbers Fair:** Imagine one student's math score is 90 and another's is 50. Their ages might be very different too.To make sure all these numbers contribute fairly to our computer's learning, we used Standard scaler. This tool adjusts all the numbers so they are on a similar scale, preventing bigger numbers from unfairly dominating the learning process. This transformation can be shown as:
   $$Z=\sigma/X-\mu$$
   - Here, X is the original value, μ is the average (mean) of all values for that feature, and σ is how spread out the values are (standard deviation). Z is the new, scaled value.
   - **Splitting the Data:** We split our big spreadsheet of student information into two parts: a "training" set and a "testing" set. The training set (80% of our data) is what our computer brain learns from, and the testing set (20% of our data) is used to check if the computer learned well, like a final exam.

2. **Training the Smart Computer Brains:** We chose two different "computer brains" (machine learning models) because sometimes one works better than the other for certain tasks.
   - **Random Forest:** Think of this as a group of many decision trees, like a forest of yes/no questions. Each tree makes its own guess, and then the forest combines all the guesses to make a super-guess. It's very good at handling different types of data.
   - **Support Vector Machine (SVM):** This model tries to find the best line (or a complex boundary) that separates students with LD from those without. It aims to make this separation as clear as possible. We used a "linear" version for simplicity.

After training, we checked how accurate each brain was on the testing data. The one that made fewer mistakes was chosen as our "best model."

3. The Web Application (User Interface):
Our web application, built using Flask, provides a user-friendly interface for students and parents to access our learning disability assessment tool. Upon creating an account and logging in, users can input a student's details through a secure form, which are then processed by our predictive model. If the prediction is affirmative, the system administers a series of multiple-choice quizzes across various subjects, including Math, Grammar, and Memory. Based on the test scores, the system identifies areas of weakness and provides personalized recommendations. The system's tailored approach enables students to receive relevant support, addressing their unique needs. By leveraging our predictive model and adaptive assessment framework, we aim to provide an effective and supportive resource for students navigating learning challenges.

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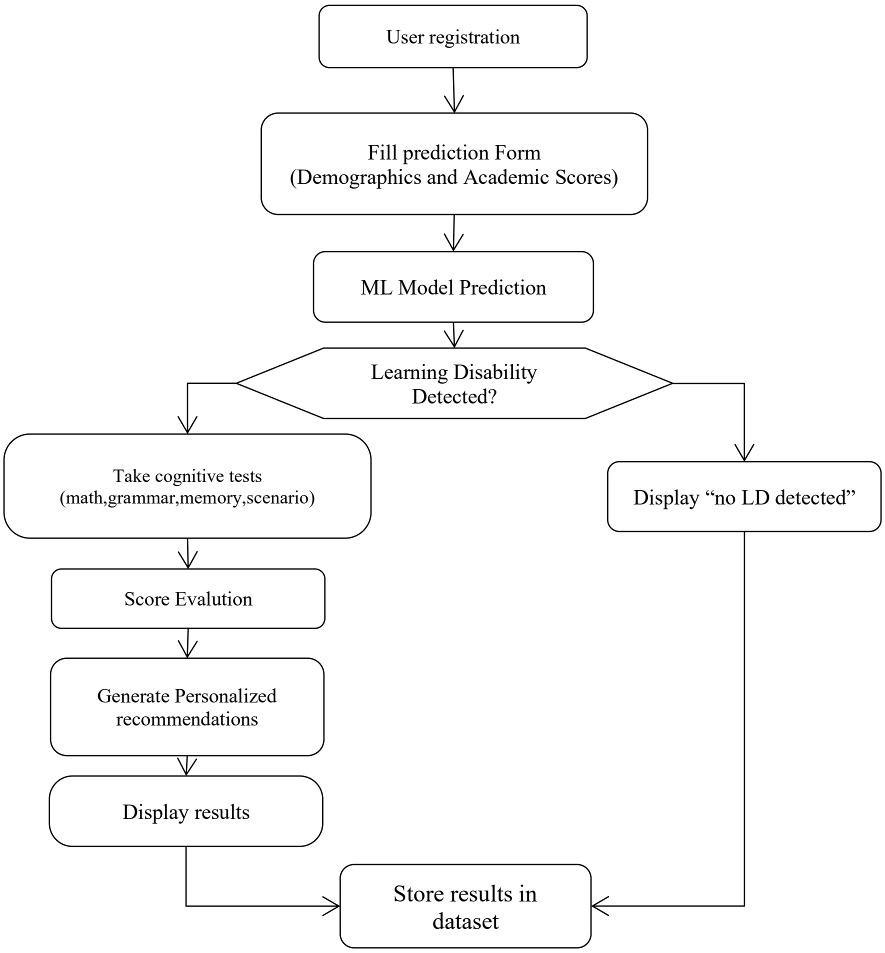

Fig 1: Workflow

The workflow begins with user authentication, followed by demographic and academic data collection. An ML model predicts learning disability risk. If detected, users complete four cognitive assessments. Based on weak areas (scores ≤2), the system generates personalized yoga and exercise recommendations, storing all results in MongoDB for tracking.

IV. RESULTS AND DISCUSSION

After putting our system together and letting our smart computer brains learn, we got some interesting results about how well they could predict learning disabilities. We trained two models, Random Forest and Support Vector Machine (SVM). When we tested them, the SVM model turned out to be a bit better. It achieved an accuracy of 91.00%. This means that 91 out of every 100 times, our SVM model correctly guessed if a student had a learning disability or not. The Random Forest model was very close, but SVM just edged it out.

Looking closer at the SVM model's performance, we checked something called the "Classification Report" and a "Confusion Matrix." Imagine you're sorting socks:

- **"No" predictions:** For students who didn't have an LD, the model was very good. It correctly said "No" most of the time (high precision and recall for 'No').
- **"Yes" predictions:** For students who did have an LD, the model also did a great job. It correctly identified them as 'Yes' about 90% of the time (90% precision and recall for 'Yes'). This is super important because we want to make sure we don't miss students who need help.

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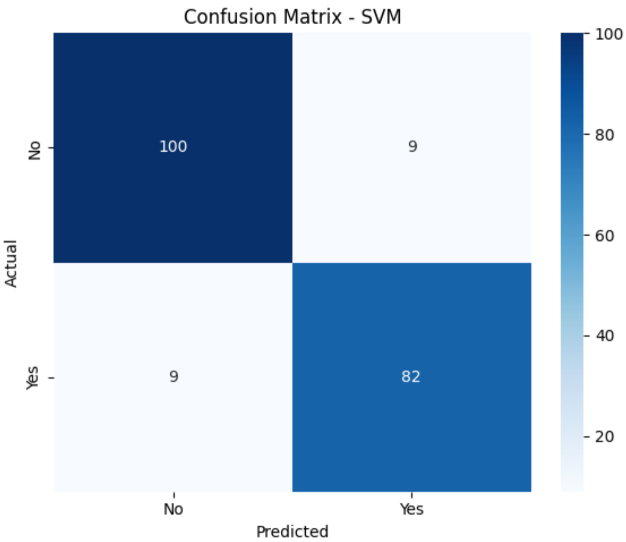

Fig 2: Confusion Matrix

The Fig 2 **Confusion Matrix** for an SVM (Support Vector Machine) model, evaluating its performance in predicting learning disabilities (LD) among students. The matrix shows that the model correctly identified 100 students without LD (true negatives) and 82 students with LD (true positives). However, it misclassified 9 students as having LD when they did not (false positives) and failed to detect LD in 9 students who had it (false negatives). These results indicate strong overall accuracy (91%) but highlight areas for improvement, particularly in reducing false negatives to ensure no LD cases are missed. Visualization helps assess the model's reliability in real-world applications, such as educational assessments.

V. CONCLUSION

Our project successfully developed an intuitive online tool to identify potential learning disabilities (LDs) in students and provide personalized support. Leveraging machine learning models, specifically Support Vector Machine (SVM) and Random Forest, we achieved a high accuracy rate of 91% with the SVM model, making it a reliable preliminary assessment tool. What sets our project apart is its comprehensive approach. Upon predicting a potential LD, the system administers targeted assessments in areas like mathematics, grammar, and memory, enabling precise identification of challenges. Based on these results, it offers tailored recommendations, including specific yoga poses to enhance focus and customized exercises to improve memory. All user data, prediction results, and assessment scores are securely stored in a database, ensuring data protection and facilitating review. By making this tool accessible online, we've bridged gaps in early assessment and targeted support, promoting inclusivity. Our project marks a significant step towards harnessing technology to empower students in their academic journey, helping them overcome obstacles and unlock their full potential.

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