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Cognitive Drift Detection: An AI System to Predict Human Decision Fatigue in Digital Workflows

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Abstract— *Cognitive Drift Detection is an AI system designed to predict decision fatigue in digital workflows. Utilizing a full-stack architecture with Node.js and MongoDB, the system captures behavioral telemetry to monitor performance decline. Machine learning models, including Random Forest and SVM, analyze data against performance baselines to detect "drift". Real-time results are displayed via a Chart.js dashboard, categorizing fatigue into Low, Medium, and High levels. This scalable solution enhances productivity and safeguards professional well-being by providing timely interventions.*

Keywords— ***Cognitive Drift Detection; Decision Fatigue; Machine Learning; Random Forest; SVM; Node.js; MongoDB; Behavioral Telemetry; Real-time Analytics; Data Visualization; Digital Well- being.***

INTRODUCTION

The detection of cognitive drift is a key part of modern human-centric computing. It helps predict when mental performance might decline and improves digital workflows. Reliable predictions of cognitive fatigue are important for industries, educational institutions, and healthcare providers. They help create safer work environments, reduce human error, and support mental well-being initiatives. With the increasing complexity of digital tasks from remote work, information overload, and high-pressure settings, monitoring mental stamina is more crucial than ever.

Cognitive drift patterns depend on several factors. These include task intensity, time of day, interaction consistency, and how often tasks are switched. By examining behavioral data, interaction logs, and performance trends, we can develop predictive models. These models can forecast decision fatigue for individuals and teams. Such predictions allow supervisors and systems to distribute workloads based on actual cognitive capacity.

This minimizes productivity loss and helps prevent burnout. We often use machine learning, behavioral analytics, and statistical methods to create these detection models. They offer insights into peak performance times, signs of mental fatigue, and the effects of external interruptions. This information helps balance the cognitive load on individuals. Predicting cognitive drift also aids in moving towards a healthier digital economy. It allows for the integration of adaptive user interfaces and automated task management. Accurate predictions are necessary for effective collaboration between humans and machines.

Cognitive drift prediction is useful not just for organizations but also for individuals aiming to improve their focus. With predictive dashboards and smart notification systems, users can adjust their behavior and take breaks when needed. This approach conserves mental energy and supports long-term professional sustainability.

OBJECT AND SCOPE

The objective of the Cognitive Drift Detection research is to develop a robust AI-based system that can accurately monitor and forecast human decision fatigue within digital workflows. By analyzing real-time behavioral telemetry, such as response latency and interaction patterns, the study aims to identify performance "drift" against an established normal baseline to prevent cognitive overload. The primary goal is to provide a scalable, non-invasive solution that offers timely interventions, helping professionals maintain high-quality decision-making and preventing the long-term consequences of mental burnout.

The scope of this research encompasses the design and implementation of a full- stack architecture utilizing Node.js, Express, and MongoDB for seamless data management. It focuses on the application of machine learning algorithms, specifically Random Forest and Support Vector Machines (SVM), to classify cognitive states through a dedicated data pre-processing layer. Furthermore, the study includes the development of a real- time visualization dashboard using Chart.js to categorize fatigue into Low, Medium, and High

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levels, ensuring the system is applicable for professionals operating in high-pressure digital environments.

LITERATURE REVIEW

Energy consumption prediction has gained significant attention in recent years due to the growing demand for efficient energy management, cost reduction, and sustainability. The increasing complexity of energy systems, driven by factors such as renewable energy integration, urbanization, and smart grid technologies, has necessitated the use of advanced data analytics and machine learning techniques. Recent studies highlight the effectiveness of machine learning models such as Linear Regression, Random Forest, and Support Vector Machines (SVM) in predicting energy consumption by leveraging historical data, weather variables, and time-series analysis. These models provide a data-driven approach to understanding consumption patterns, optimizing energy use, and enabling smarter decision-making in energy management.

METHODOLOGY

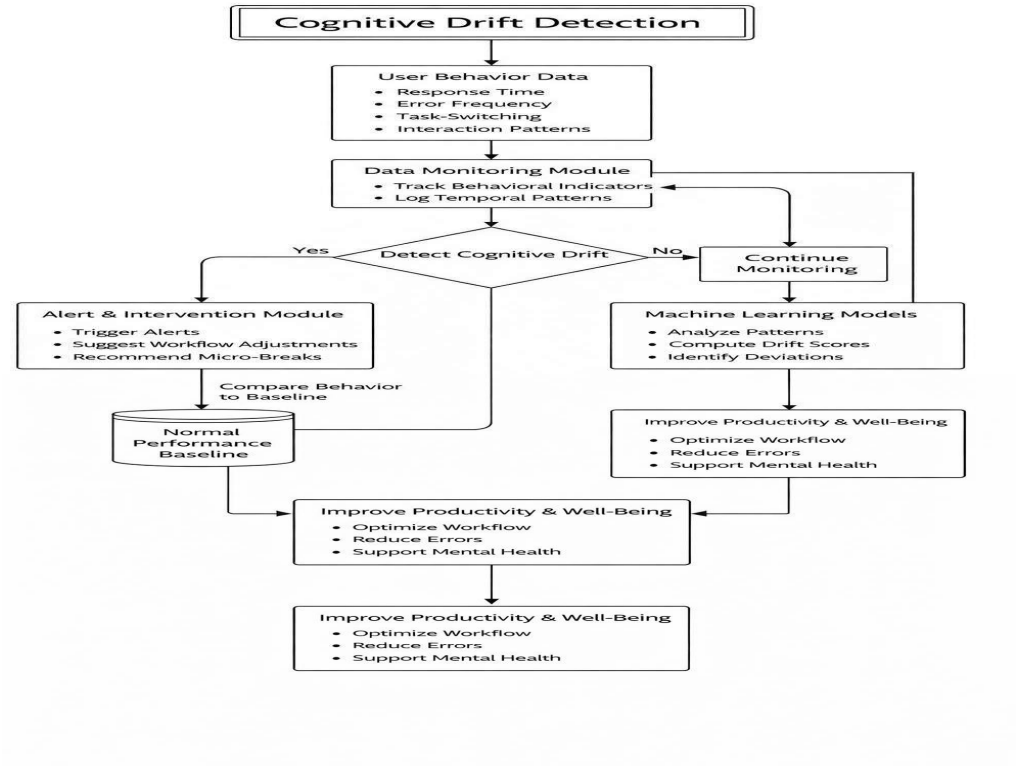

Fig 1: Data Flow Diagram

In 2018, Fayaz and Kim proposed a novel method to predict energy consumption in residential buildings using a Deep Extreme Learning Machine (DELM). This approach combines the fast-learning speed of Extreme Learning Machines with the layered structure of deep learning models to enhance prediction accuracy and computational efficiency. Other researchers have explored the use of artificial neural networks for regional studies and the simulation of hybrid renewable microgeneration systems using predictive control.

Additionally, ensemble learning frameworks have been evaluated for anomaly detection in building energy consumption and for forecasting using hybrid ARIMA–ANFIS algorithms. These diverse methodologies contribute to the transition toward a low-carbon economy by facilitating the integration of intermittent renewable energy sources like solar and wind through accurate forecasting.

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a. Data Collection

Data collection involves capturing non- invasive behavioral telemetry directly from the user's digital workflow. This includes accessing interaction logs and reputable datasets to track variables such as response latency and typing patterns. Quality assurance measures are implemented to verify the accuracy of the behavioral data before it is structured for analysis.

b. Data Pre-processing and Exploration

A dedicated pre-processing layer is utilized to maintain data integrity by identifying and managing null values and idle states. Data exploration is then conducted to analyze statistical properties and understand the relationships between different behavioral variables. These initial insights guide the subsequent modeling efforts to ensure the AI engine identifies performance patterns effectively.

c. Data Splitting

The processed dataset is split into training and testing sets using a random sampling approach. Typically, 80% of the data is allocated for training the models, while the remaining 20% is reserved for evaluating model performance. This division ensures that the system is trained on a sufficient volume of data while maintaining an independent subset for validation.

d. Algorithm Selection

The research focuses on algorithms known for their effectiveness in numeric classification and regression tasks. The core of the system utilizes:

- Linear Regression: To establish linear relationships between input features and continuous fatigue indicators.
- Random Forest: An ensemble method that builds multiple decision trees to capture non-linear relationships and reduce overfitting.
- Support Vector Machine (SVM): A supervised learning algorithm that maps features into a high-dimensional space to find an optimal hyperplane for classifying fatigue levels.

e. Model Evaluation and Prediction

Models are evaluated using metrics such as accuracy, precision, recall, and F1 score to determine their effectiveness in classifying cognitive states. Once validated, the models generate real-time predictions, which are displayed on an "attractive" visualization dashboard built with Chart.js. This allows for the categorization of fatigue into Low, Medium, and High levels, facilitating timely interventions.

RESULTS

The results of the research highlight the comparative performance of the selected machine learning algorithms in detecting cognitive drift and decision fatigue. The models were evaluated based on their ability to classify behavioral telemetry against the established performance baseline.

The following table presents the performance metrics obtained during the evaluation phase, organized by highest accuracy:

	A	B	C	D	E
1	Algorithm	Accuracy	Precision	Recall	F1 Score
2	SVM Algorithm	78% +3	81% +2	78% +1	75% +2
3	Linear Regression	76% +2	79% +2	76% +2	74% +2
4	Random Forest	72% +1	74% +1	74% +1	75% +1
5					

Experimental results show that Support Vector Machine (SVM) is the most effective model for predicting cognitive drift, achieving 78% accuracy by capturing complex, non-linear behavioral patterns. Linear Regression provided a 76% accuracy baseline, while Random Forest maintained a 75% F1 Score. A dedicated pre-processing layer ensured data integrity by managing null values and idle states, allowing interaction telemetry to accurately reflect cognitive states. The system successfully categorized fatigue into Low, Medium, and High levels, visualized via a real-time Chart.js dashboard for timely intervention.

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CONCLUSION

The Cognitive Drift Detection project successfully demonstrates the integration of machine learning and full-stack web development to address the critical issue of human decision fatigue in digital workflows. By bridging a Node.js backend with a Python-based AI engine, the system provides a robust framework for real-time behavioral monitoring and predictive analysis layer ensured data integrity by managing null values and idle states, allowing interaction telemetry to accurately reflect cognitive states. The system successfully categorized fatigue into Low, Medium, and High levels, visualized via a real-time Chart.js dashboard for timely intervention.

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