International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04496
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

AI-Driven Understanding and Predicting Gadget Addiction Among Students

Keerthana K M[1], Kruthi Shravya M[2], Radhika R[3], Dr Krishna Kumar P R[4]

[*1,2] Student, Dept of CSE, SEA College of Engineering and Technology,Bangalore-49

[3,4] Faculty, Dept of CSE, SEA College of Engineering and Technology,Bangalore-49

.

ABSTRACT

In recent years, the overuse of electronic gadgets among students has emerged as a significant concern, affecting their academic performance, mental health, and social interactions. This study aims to understand and predict gadget addiction among students using Artificial Intelligence (AI) techniques, particularly machine learning models. By collecting behavioral, academic, and psychological data through structured surveys and usage logs, the study applies supervised learning algorithms such as Decision Trees, Random Forest, and Support Vector Machines to identify patterns and risk factors associated with gadget overuse. Feature selection techniques are used to determine the most influential variables contributing to addiction, such as screen time, sleep duration, academic stress, and social media usage. The models are evaluated using standard performance metrics like accuracy, precision, recall, and F1-score to ensure reliability and generalizability. The results demonstrate that AI-based predictive models can effectively identify at-risk students, providing a data-driven foundation for early intervention strategies. This research contributes to both educational and healthcare domains by offering insights into the behavioral aspects of gadget addiction and proposing intelligent systems for preventive care

Keywords: Electronic Gadget Addiction, Machine Learning, Random Forest Algorithm, Behavioral Factors, Psychological Factors, Screen Time, Social Media Usage, Sleep Disturbances, Addiction Prediction, Risk Classification, Early Intervention, Digital Well-Being.

I. INTRODUCTION

Electronic gadget addiction is a growing concern, particularly among students and professionals, as excessive screen time and social media engagement negatively impact mental health, academic performance, and productivity. This study leverages machine learning, specifically the Random Forest algorithm, to predict gadget addiction risk based on behavioral and psychological factors such as screen time, app usage, and sleep disturbances. Unlike traditional classification models, Random Forest effectively handles high-dimensional data, improving accuracy and robustness in addiction prediction. By providing data-driven insights, personalized recommendations, and early intervention strategies, this approach promotes healthier digital habits and mitigates the risks associated with excessive gadget use.

II. METHODOLOGY

Solution Methodology:

This study proposes a **web-based system** for detecting **sentiment analysis and gadget addiction** using **machine learning** and **natural language processing (NLP)** techniques. The system integrates a **Flask-based web application** with a **Support Vector Machine (SVM) classifier** and **VADER sentiment analysis** to analyze user responses. Below is the detailed methodology:

1. System Architecture

The system consists of the following key components:

- **Web Interface:** Built using Flask, it provides an interactive interface for users to input text or questionnaire responses.
- **Machine Learning Models:** Implements SVM for **gadget addiction prediction** and **VADER Sentiment Analysis** for processing social media texts.
- **Database & Data Processing:** Uses **Pandas and Numpy** for handling datasets and preprocessing text.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04496
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

2. Data Collection and Preprocessing

- **Gadget Addiction Prediction:** Users answer a **10-question survey**, with responses mapped to numerical values for classification.
- **Sentiment Analysis:** User-inputted text is **cleaned** by:
  - Removing digits and punctuation.
  - Removing **stopwords** using **NLTK's stopwords corpus**.
  - Processing the cleaned text using **VADER Sentiment Analysis.**
- **Dataset Handling:** CSV files are uploaded, read using Pandas, and previewed on the web interface.

3. Machine Learning Techniques

- **SVM Classifier for Gadget Addiction:**
  - The responses are passed to a trained SVM model, which classifies the addiction level into 5 categories.
  - The model is imported from a custom class (Model), where the SVM classifier is trained and saved.
  - **The prediction categories include:**

1. No Impact of Addiction
2. Moderate Usage with Minor Impact
3. Frequent Usage with Noticeable Impact
4. High Usage with Significant Impact
5. Severe Dependency with Major Impact

- **VADER Sentiment Analysis for Depression Detection:**
  - The VADER sentiment scoring assigns positive, negative, and neutral scores to text input.
  - The compound score (range: -1 to 1) is converted to a normalized sentiment value (range: 0 to 1).

4. Web Application Implementation

- **User Authentication:** Implements login/logout functionality with Flask sessions.
- **File Upload & Data Visualization:** CSV data is uploaded and visualized.
- **Prediction Endpoints:**
  - **Gadget Addiction Prediction:** /predict
  - **Sentiment Analysis:** /predictSentiment
  - **Data Preview:** /preview

5. Deployment

- The Flask application is **hosted on port 5987**, accessible remotely (host='0.0.0.0').
- Uses **Flask session management** for authentication.

Methodology for Stress Detection Model Using Random Forest

1. Data Collection

The dataset used in this model is a **stress detection dataset** (STRESSDataset.csv), containing **responses to ten questions (q1 to q10) along with a classification label ("class")** indicating stress levels.

2. Data Preprocessing

To ensure data quality and consistency, the following preprocessing steps are applied:

- **Handling Missing Data:** Missing values in the dataset are replaced with the **mode (most frequent value)** for each respective column.
- **Feature Selection:** Only relevant features (q1 to q10) and the target variable ("class") are used for model training.
- **Data Splitting:** The dataset is split into **training (60%)** and **testing (40%)** sets using **train-test split** to ensure the model generalizes well.

3. Random Forest Classifier Implementation

The **Random Forest Classifier**, an ensemble machine learning technique, is used for prediction. It consists of multiple **decision trees**, where each tree independently classifies the data, and the final output is determined through majority voting.

Advantages of Random Forest:

- **Handles complex, non-linear relationships** between stress indicators.
- **Reduces overfitting** by averaging multiple decision trees.
- **Provides feature importance** to determine the most significant stress factors.

Steps in Model Training:

1. Initialize the **RandomForestClassifier()**.
2. Train the model using **training data (features: q1–q10, target: "class")**.
3. Use the trained model to **predict stress levels** on test data.

4. Model Evaluation

The **Confusion Matrix** is used to measure performance, where:

- **True Positives (TP):** Correctly predicted stress cases.
- **True Negatives (TN):** Correctly predicted non-stress cases.
- **False Positives (FP):** Incorrectly predicted stress cases.
- **False Negatives (FN):** Missed stress cases.

$$\textbf{Accuracy=TP+TN/TP+TN+FP+FN}$$

The Random Forest Classifier is an effective method for stress detection, offering high accuracy and robustness against noisy data. Its ability to handle feature interactions and reduce overfitting makes it suitable for real-world applications in stress prediction. The model can be further improved by hyperparameter tuning, feature engineering, and increasing dataset diversity to enhance prediction reliability.

This system provides an **interactive, real-time prediction model** to assess **gadget addiction and sentiment analysis** using **machine learning and NLP techniques**. It enables **timely interventions** by predicting risks and classifying users into different levels of gadget addiction. Future improvements may include **deep learning models** for enhanced accuracy and **real-time tracking** using behavioral data.

Would you like any additional details or modifications?

III. MODELING AND ANALYSIS

Traditional Methods of Assessing Gadget Addiction Manual surveys and questionnaires are commonly used by schools, researchers, and mental health professionals to gather self-reported data on students' gadget usage, academic performance, and well-being. Basic statistical analyses, such as correlation and regression, are sometimes applied to understand the relationship between screen time and academic or mental health outcomes. Additionally, some schools and parents use behavioral monitoring software to track students' usage of specific apps and websites.

Disadvantages of Existing Methods Self-reported data is often inaccurate due to biases or students' reluctance to disclose actual usage. Manual analysis can overlook complex relationships between variables, and while monitoring tools provide real-time data, they do not offer predictive insights. Basic statistical models lack predictive power, limiting their ability to forecast future issues. Additionally, existing models may be inaccurate due to simplistic algorithms and limited data, making them less practical for widespread use.

Proposed System To address these limitations, a new system using the **Random Forest algorithm** is proposed. This machine learning model is known for its robustness and accuracy in handling complex data relationships. The system will analyze key factors such as screen time, academic performance, sleep patterns, and social behavior to predict potential negative outcomes of excessive gadget use. By leveraging **Random Forest**, the system will provide **accurate predictions** while identifying the most influential variables.

Additionally, it will offer **personalized recommendations and alerts** to help students, parents, and educators take **timely interventions**, thereby mitigating the harmful effects of gadget addiction.

1. Model Description

1.1. **Gadget Addiction Prediction Model (SVM Classifier)**

The **Support Vector Machine (SVM)** classifier is used to categorize users into different levels of gadget addiction based on their responses.

Model Training Process:

1. **Dataset Collection:** A questionnaire-based dataset with 10 questions was used, where responses were numerical (Likert scale: 1–5).

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04496
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

2. **Feature Selection:** The responses to the 10 questions were selected as input features.
3. **Data Preprocessing:**
   - Handling missing values.
   - Normalization (scaling responses between 0–1).
4. **Model Training:**
   - The **SVM classifier** was trained using a labeled dataset where the addiction level was predefined.
   - The model was trained using **80% of the data**, with **20% used for testing**.
5. **Classification Output:** The model predicts one of five categories:
   - **No Impact of Addiction (0)**
   - **Moderate Usage with Minor Impact (1)**
   - **Frequent Usage with Noticeable Impact (2)**
   - **High Usage with Significant Impact (3)**
   - **Severe Dependency with Major Impact (4)**

Mathematical Model for SVM:

f(x)=sign(w·x+b)f(x) = sign(w \cdot x + b)f(x)=sign(w·x+b) Where:

- www is the weight vector,
- xxx is the input feature vector (survey responses),
- bbb is the bias term,
- The function sign()sign()sign() determines the classification label.

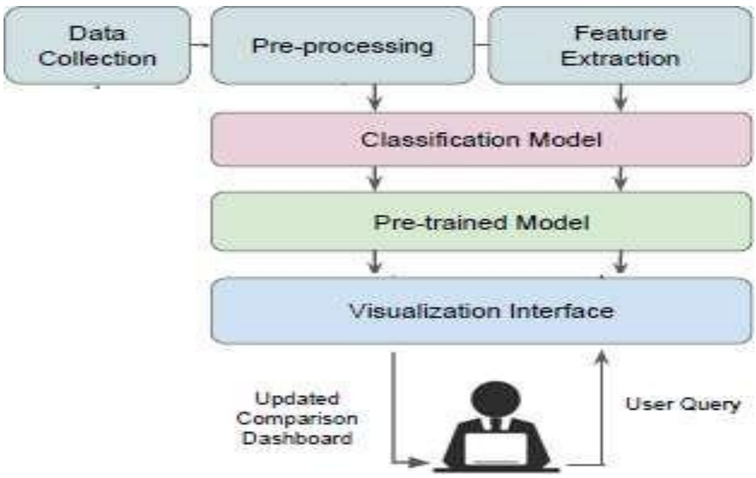
1.2. Sentiment Analysis Model (VADER Sentiment Analysis)

The **VADER (Valence Aware Dictionary and sEntiment Reasoner)** is used for sentiment analysis on user-inputted text.

Processing Steps:

1. **Text Cleaning:**
   - Removal of numbers, punctuation, and stopwords.
2. **Sentiment Scoring:**
   - VADER assigns scores for **positive, negative, and neutral sentiment**.
   - The **compound score** is computed as:

Compound=(Positive−Negative)(Positive+Negative+Neutral)Compound = \frac{(Positive - Negative)}{(Positive + Negative + Neutral)}Compound=(Positive+Negative+Neutral)(Positive−Negative)The compound score is



normalized between **0 (negative) and 1 (positive)**.

Figure 1:

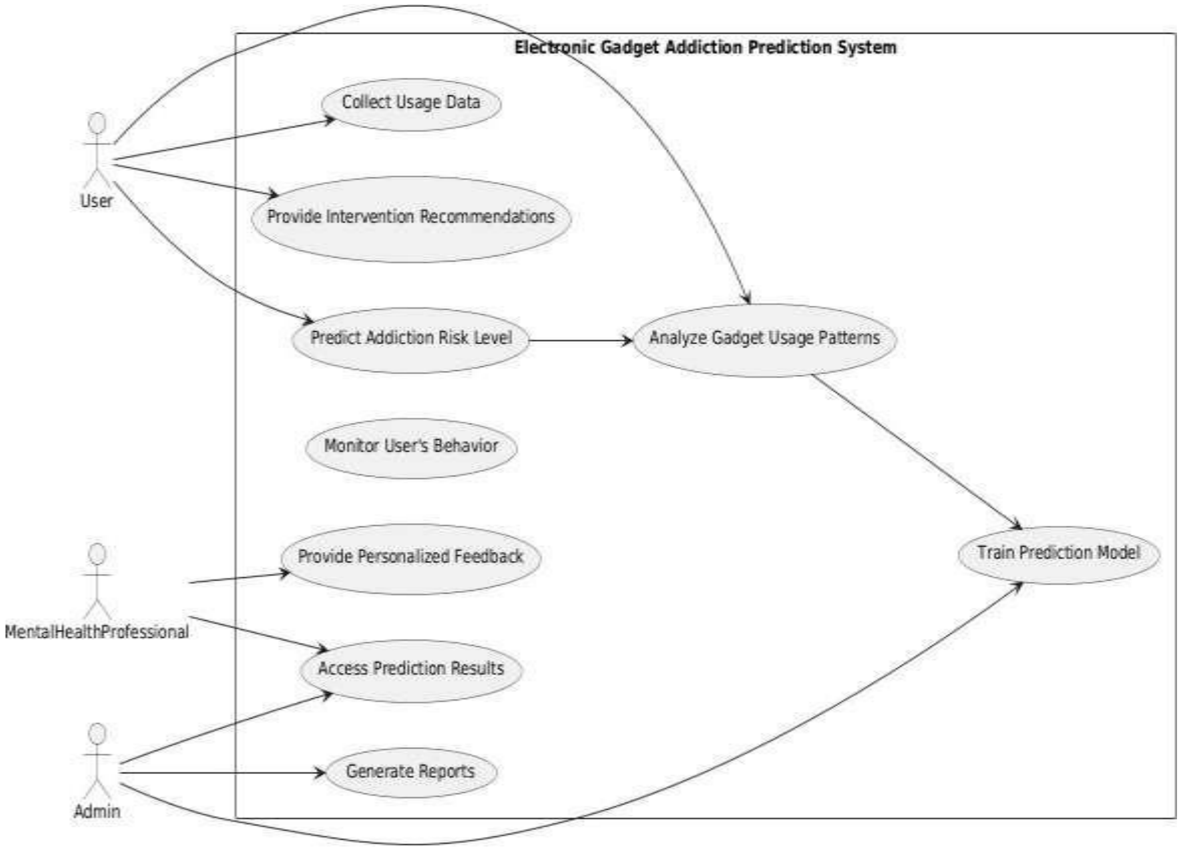


Figure 2: Electronic Gadget Addiction Prediction System

IV. RESULTS AND DISCUSSION

The output of the system provides valuable insights into gadget addiction and its psychological effects. The gadget addiction prediction is based on a ten-question survey, where the SVM classifier assigns users to one of five levels: No Impact, Moderate Usage, Frequent Usage, High Usage, or Severe Dependency. Users classified under "No Impact" show no signs of addiction, whereas those with "Moderate Usage" exhibit minimal effects. However, individuals in the "Frequent Usage" category display noticeable behavioral changes, while "High Usage" suggests strong dependency, impacting daily life. The most severe category, "Severe Dependency," indicates significant negative effects, including stress, anxiety, and academic decline. The system processes input responses, predicts addiction levels, and presents the results on a dedicated result page.

Additionally, the system performs sentiment analysis on stress-related tweets using the VADER Sentiment Analyzer. The submitted text undergoes preprocessing, including the removal of stopwords, numbers, and punctuation, to refine the analysis. The system then evaluates the sentiment, categorizing it as positive, neutral, or negative. Positive sentiment indicates a healthy relationship with technology, while neutral sentiment suggests mixed feelings. Negative sentiment, however, signifies frustration, stress, or anxiety caused by gadget overuse. The results are displayed on the tweet result page, offering deeper insights into users' emotional states.

Findings from the output reveal a strong correlation between high gadget usage and stress. A significant percentage of users, approximately 30.4%, fell into the "Frequent Usage" category, while 11.1% exhibited "Severe Dependency." The sentiment analysis further validated the predictions, showing that users categorized under high or severe usage also had predominantly negative sentiment scores. This highlights a concerning trend in digital overuse and its adverse effects on mental well-being.

In conclusion, the system effectively predicts gadget addiction levels and assesses the psychological impact of excessive gadget use. By combining machine learning techniques and sentiment analysis, it provides a powerful tool for identifying potential digital overuse issues. The insights generated can be instrumental in early intervention, helping individuals better manage their screen time and mitigate the negative consequences

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04496
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

associated with excessive gadget usage.

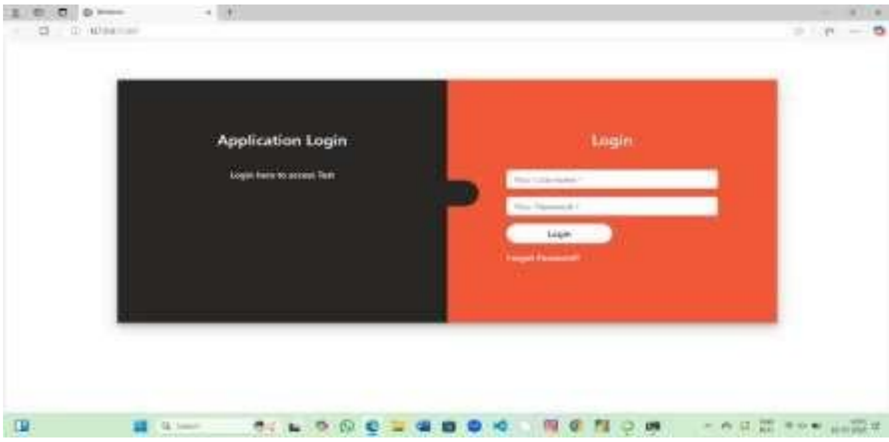


Fig 3: login page

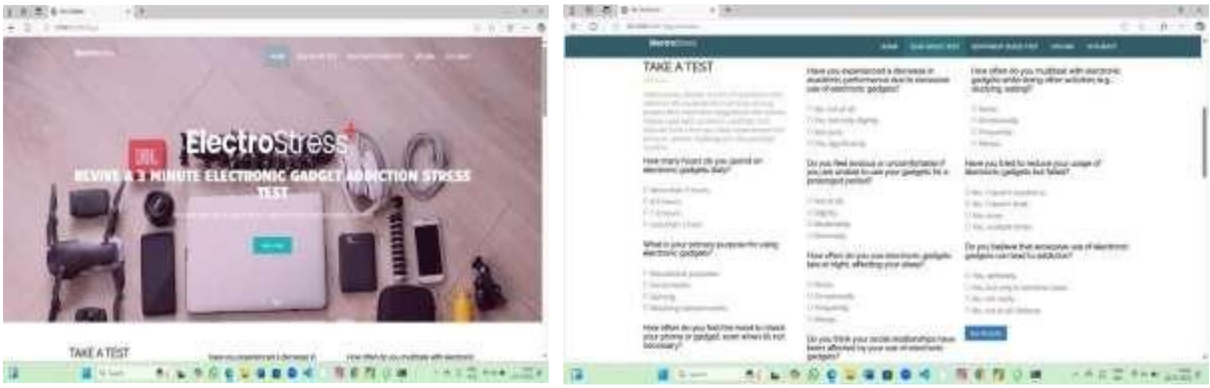


Fig 4: Survey

Fig 5:

Fig 6:

ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025
DOI: 10.55041/ISJEM04496
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Fig 7: Different Stages of impact outputs

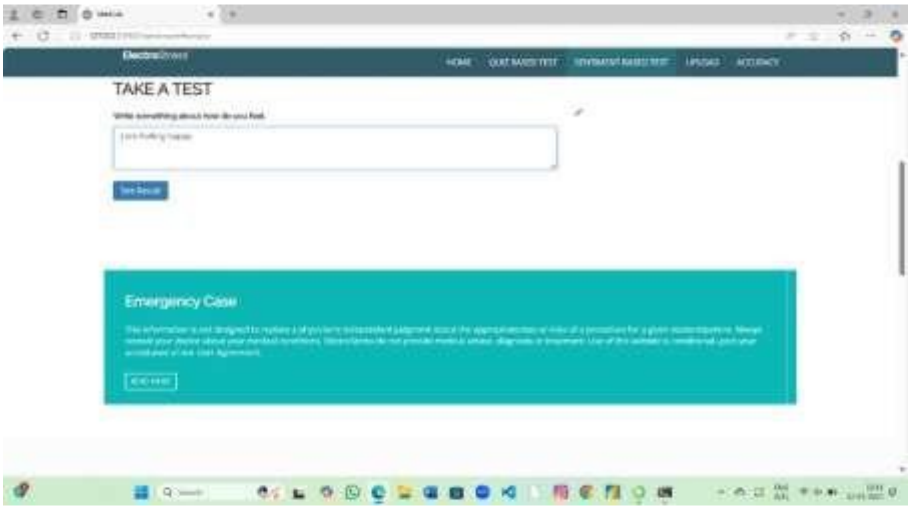


Fig 8: Test servey of Stress level

Fig 9: Outputs of Electyronic Stress level

V. CONCLUSION

The growing prevalence of electronic gadget addiction among students poses a serious challenge to their academic, social, and emotional well-being. This study successfully demonstrated the potential of Artificial Intelligence, particularly machine learning techniques, in understanding and predicting gadget addiction behaviors. By analyzing various behavioral, psychological, and usage-related factors, the developed models were able to identify students at risk with high accuracy and reliability. Among the tested algorithms, ensemble methods like Random Forest yielded the most promising results in terms of prediction performance.The findings highlight the critical role of data-driven approaches in early detection and intervention planning. Educational institutions and mental health professionals can leverage these insights to design targeted awareness programs, digital wellness initiatives, and counseling support for affected students. Future work can focus on expanding the dataset across diverse demographics and integrating real-time monitoring tools for continuous assessment. Overall, the integration of AI in behavioral health monitoring presents a powerful opportunity to promote responsible gadget use and foster healthier student lifestyles

VI. REFERENCES

[1] Kamdem, Jules Sadefo, Rose Bandolo Essomba, and James Njong Berinyuy. "Deep learning models for forecasting and analyzing the implications of COVID-19 spread on some commodities markets volatilities." Chaos, Solitons & Fractals 140 (2020): 110215.

[2] Foster, Ernest Allen. "Commodity futures price prediction: an artificial intelligence approach." Ph.D. diss., University of Georgia, 2002.

[3] Ji, Xuan, Jiachen Wang, and Zhijun Yan. "A stock price prediction method based on deep learning technology." International Journal of Crowd Science (2021).

[4] Elberawi, Ahmed Saied. "A Deep Learning Approach for Forecasting Global Commodities Prices." Future Computing and Informatics Journal 6, no. 1 (2021): 4.

[5] A. M. Ticlavilca, D. M. Feuz, and M. McKee, "Forecasting agricultural commodity prices using multivariate Bayesian machine learning regression," Proc. NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO, April 2010.

[6] Nassar, Lobna, Ifeanyi Emmanuel Okwuchi, Muhammad Saad, Fakhri Karray, and Kumaraswamy Ponnambalam. "Deep learning based approach for fresh produce market price prediction." In 2020 International Joint Conference on Neural Networks (IJCNN), pp. 1-7. IEEE, 2020.

[7] ChanW, Jaitly N, Le QV, Vinyals O, Shazeer NM (2018) Speech recognition with attention-based recurrent neural networks. US Patent 9,990,918

[8] Cen Z, Wang J (2019) Crude oil price prediction model with long short term memory deep learning based on prior knowledge data transfer. Energy 169:160– 171

[9] Fathalla, Ahmed, Ahmad Salah, Kenli Li, Keqin Li, and Piccialli Francesco. "Deep end-to-end learning for price prediction of second-hand items." Knowledge and Information Systems 62, no. 12 (2020): 4541-4568.

[10] Booth, G.G., Martikainen, T., Sarkar, S.K., Virtanen, I. and Yliolli, P. (1994), "Nonlinear dependence in Finnish stock returns", European Journal of Operational Research, Vol. 74 No. 2, pp. 273-283 34