Enhanced Stress Detection Through Deep Learning Techniques

PALLAGANI VENU GOPAL[1], KUNDETI ANURADHA[2], VADDI SAI MANIKANTA[3], KAJA NARESH BABU[4], VUKANTI DIVYA TEJA SAI[5]

#1 Associate Professor of theCSE (Data Science) Department of NRI INSTITUTE OF TECHNOLOGY.

#2,#3,#4,#5 Student B.Tech program in Computer Science and Engineering with a specialization in Data Science at NRI Institute of Technology.

ABSTRACT_ Stress can have a severe physical and mental health impact if it is not appropriately evaluated and handled. Existing approaches for identifying stress, such as surveys or simple sensor-based systems, frequently lack precision and real-time monitoring. This study provides a new way to stress monitoring that takes advantage of advances in deep learning technology. Physiological and behavioral data acquired from wearable or mobile sensors was used to evaluate self-reported stress. However, relying on self-reports for stress annotation during studies frequently results in a lack of labeled data, hindering the development of effective and widely applicable stress prediction models. In contrast, sensors can continuously capture signals without the need for annotations.

Researchers attempted to identify stress using standard machine-learning approaches for assessing physiological signals. The achieved results, which range from 50% to 90% accuracy, have yielded mixed results. One disadvantage of classic machine learning algorithms is their reliance on manually created features. When these traits are incorrectly detected, accuracy suffers. To address this restriction, we developed a deep neural network technique. Deep neural networks reduce the need for hand-crafted features, extracting relevant features straight from raw data via the network's layers. In this study, we used deep neural networks to assess physiological data from the DRYAD dataset. The goal included multi-class classification for stress detection, in which the networks differentiated between low-stressed, medium-stressed, and high-stressed states, effectively identifying baseline, stressed, and amused.

1.INTRODUCTION

Stress is something many individuals experience no matter what their experience. It's the bodys reaction, to challenges whether they're physical or mental. Despite the fact that some stress can sometimes force us to do a lot, chronic stress can cause a variety of health issues. Constant pressure can add to conditions like uneasiness, discouragement, heart issues, weight and mental troubles. That is the reason it's significant to watch out for our feelings of anxiety for both our psychological prosperity. Self-reported assessments were frequently used in the past for stress monitoring. In any case, these strategies are emotional. Try not to give constant bits of knowledge into how our bodies answer pressure. A methodologies have utilized gadgets to follow things like pulse and skin temperature as signs of feelings of anxiety. These techniques may not generally be exact because of variables that can influence these estimations.

Man-made reasoning has gained ground in fields by using profound learning strategies. Using data from sources like images, videos, audio recordings, and sensor data, deep learning has shown promise in computing and health monitoring tasks like recognizing emotions, detecting pain, and estimating workload. The development of a learning system for precise instantaneous and subtle stress tracking is the primary objective of this study. Our imaginative technique blends biosensors with PC vision data to measure pressure responses utilizing signals from wearables and to accumulate exhaustive logical clues, from looks, actual developments, and activities. We made some development profound learning models to foresee pressure through various variables.

Stress frequently shows the presence of fundamental ailments. Stress can be brought about by different variables, like sickliness, wretchedness, congestive coronary illness, hypothyroidism, solid effort, weight, narcolepsy, allergy meds, sleep deprivation, and tuberculosis. Normal side effects of pressure incorporate dry skin, fragile hair, unnecessary thirst, successive pee, windedness, and weakness. There are two primary sorts of pressure: mental stress, which is connected to emotional or psychological factors, and physical stress, which comes from physical activities like lifting, playing, or prolonged running. During this period, mental pressure is a typical event and has been related with reduced execution on mental tests It likewise impacts human-related mishaps and wounds, prompting diminished work efficiency, dynamic challenges, and rest unsettling influences. Intense mental pressure is accepted to add to a preliminary and ventricular arrhythmias, which can be made sense of utilizing electrophysiological standards and electrical sign handling strategies, like the Body Temperature(BT),Inter-Thump Stretch (IBI), Pulse (HR), BloodVolumePulse (BVP), and Electrodermal Movement (EDA).

2.LITERATURE SURVEY

A comprehensive literature review on stress monitoring would involve examining studies across various disciplines such as psychology, medicine, engineering, and neuroscience. It would encompass research on different methods and technologies used for measuring and assessing stress levels, including both physiological and psychological approaches.

Physiological indicators commonly studied in stress monitoring research include:

Heart rate variability (HRV): Research has shown that changes in HRV can reflect autonomic nervous system activity and are often associated with stress.

Cortisol levels: Cortisol, known as the "stress hormone," can be measured through saliva, blood, or urine samples to assess the body's physiological response to stress.

Skin conductance (electrodermal activity): Changes in skin conductance can indicate sympathetic nervous system arousal, making it a valuable measure in stress monitoring.

Psychological measures used in stress monitoring research include self-report questionnaires, interviews, and behavioral assessments. These measures aim to capture subjective experiences of stress, coping strategies, and perceived stress levels.

The literature review would also explore the applications of stress monitoring in various settings, such as healthcare, occupational health and safety, sports performance, and consumer wearables. For example, stress monitoring technology integrated into wearable devices allows for continuous monitoring of stress levels in real-time, offering opportunities for personalized interventions and self-management strategies.

Additionally, the review would discuss the challenges and limitations associated with stress monitoring, including issues related to accuracy, reliability, and validity of measurements, as well as ethical considerations regarding privacy and data security. Future directions for research could include the development of novel sensors and algorithms for improved stress detection, as well as the integration of multi-modal approaches combining physiological and psychological measures for a more comprehensive understanding of stress dynamics.

In the ongoing pursuit of advancements in stress monitoring technologies, leveraging various physiological signals has been pivotal. This literature review focuses on recent studies that have contributed significantly to the field by employing a range of datasets, and algorithms, and achieving varied levels of accuracy in stress detection. The primary aim is to contextualize our study within the current landscape, particularly highlighting our work with the DRYAD dataset and our proposed model.

Wearable Stress and Affect Detection (WESAD) with Support Vector Machine (SVM) [2023]

In a notable study by in 2023, the WESAD dataset was employed to utilize the Support Vector Machine (SVM) algorithm for stress detection, achieving an accuracy of 80%. The WESAD dataset is comprehensive, incorporating multiple physiological signals, which provides a rich foundation for stress analysis. The use of SVM, a well-established machine learning algorithm known for its effectiveness in classification tasks, underscores the ongoing relevance of traditional algorithms in handling modern-day stress detection challenges.

Multimodal Physiological Signal Analysis [2022]

Research conducted in 2022 by took a multimodal approach by incorporating a combination of ECG, EDA, PPG, and RESP signals to diagnose stress levels. The study employed the K-Nearest Neighbors (KNN) algorithm, achieving a high accuracy rate of 96%. This study highlights the potential of multimodal physiological data in enhancing the accuracy of stress detection systems. The success of the KNN algorithm in this context also demonstrates its robustness and adaptability in handling diverse data types.

EEG-Based Stress Detection Using RN-CNN [2020]

The study by in 2020 introduced an innovative approach by applying a Recurrent Neural Network-Convolutional Neural Network (RN-CNN) hybrid model to EEG data for stress detection, attaining an accuracy of 92.95%. This work underscores the potential of combining traditional and deep learning techniques to improve the interpretability and performance of stress detection models, especially when dealing with complex signals like EEG.

LDA Analysis of Multimodal Signals [2021]

In 2021,explored the effectiveness of Linear Discriminant Analysis (LDA) on a combination of ECG, EDA, PPG, and RESP signals, achieving an 85% accuracy rate. This study exemplifies the ongoing relevance of classical statistical methods in the field of stress detection, particularly when applied to a comprehensive set of physiological signals.

Deep Convolutional Selective Autoencoder Network (DCSAEN) for EEG[2020]

Another significant contribution was made by in 2020, employing a Deep Convolutional Selective Autoencoder Network (DCSAEN) for EEG-based stress detection, resulting in an 81.5% accuracy. This study is notable for its focus on deep learning architectures and their application in extracting meaningful features from EEG signals, which are inherently complex and noisy.

Our Contribution: DRYAD Dataset with Proposed Model

Building upon the foundation laid by these studies, our research introduces a novel model applied to the DRYAD dataset for stress detection. While the aforementioned studies have significantly advanced the field, our work aims to address some of the gaps and challenges they present, particularly in terms of model generalizability and efficiency. Our proposed model is designed to optimize performance, leveraging the strengths of the techniques highlighted in prior works while introducing new strategies to enhance accuracy and applicability in real-world scenarios.

In summary, the landscape of stress monitoring using physiological signals is both broad and deep, with various datasets and algorithms showing promise. Our research on the DRYAD dataset with a proposed model contributes to this evolving field, aiming to push the boundaries of what's possible in stress detection accuracy and reliability.

3.PROPOSED SYSTEM

Creating a stress monitoring system requires combining many technologies, methodologies, and approaches to measure, assess, and manage stress. In the suggested system, we apply deep learning approaches to achieve higher outcomes and accuracy than the above or existing algorithms. To prepare the data for the machine learning model, we started by preprocessing it. Initially, we thoroughly examined the dataset for any missing values. To guarantee data consistency, they were promptly eliminated. Following that, we used normalization to standardize the data and scale it. For our classification task, we used K Means Clustering to categorize stress into three levels

We used this labeled dataset to train our learning model. Our solution is based on a Bidirectional Long Short Term Memory (Bi LSTM) model, which is well-known for its ability to detect data dependencies. This layer consists of 32 layers that have been included into the model's structure. Unlike LSTMs, which evaluate sequences in one way, the bidirectional version can recognize patterns from both past and future contexts, boosting its ability to interpret subtle temporal correlations within stress data.

3.1 IMPLEMENTATION

After finishing the data collection phase the next crucial step involves prepping the data. When examining the dataset it was noted that there was a spread of data points, across various categories with some categories having more values than others. The algorithms are used K-Means clustering, Handling imbalanced data with SMOTE, and Bi-LSTM.

K-Means Clustering:

K-means clustering algorithm, a well-liked technique for learning without supervision. The panda's library is used to manage data in the method, while sklearn. Cluster is used to access the KMeans algorithm. The dataset, which includes several measurements (features as BVP, EDA, HR, IBI, and TEMP), is presumably preprocessed. The cluster assignments are then added to the dataset as target values in a new column called target. By offering insights into the data's innate groupings, this cluster information enrichment of the dataset facilitates additional analytical or machine learning initiatives.

Handling Imbalanced Data with SMOTE:

Imbalanced data is an issue, in machine learning when there's a distribution of instances among different classes. To tackle this the Synthetic Minority Over Sampling Technique (SMOTE) can be used. When datasets are unbalanced, it can lead to models that favor the majority class impacting the fairness and overall performance of the model in classification tasks. SMOTE is a method for boosting the minority class. It operates through the imblearn. Over_sampling module by selecting examples from the existing minority class and generating ones that are slightly different but still comparable. By balancing out the class distribution this technique enhances the dataset's suitability, for training models that deliver performance across all classes.

Bi-directional Long Short-Term Memory (Bi-LSTM):

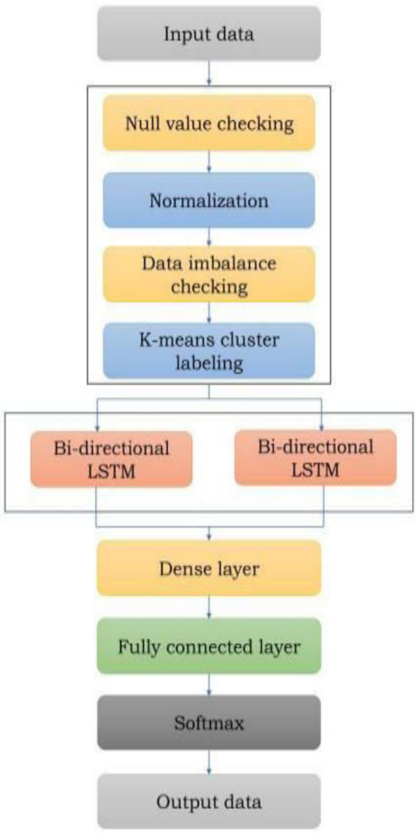
The Bi-LSTM model, unlike LSTM models, processes sequences in both forward. Reverse directions simultaneously. This bidirectional approach allows the model to analyze information from future contexts improving its capability to identify patterns within sequential data effectively.

- Consisting of two layers that assess the input sequence in forward and reverse order the Bi LSTM merges information from these layers to generate a cohesive output representation that considers both temporal directions. To enhance the model further a connected dense layer with 32 units follows the Bi LSTM layer.

This added complexity increases the model's capacity to depict relationships in data. The SoftMax activation function is then used to assign probabilities to stress level categories for multi-class classification. This research introduces an architecture centered around the powerful Bi LSTM structure for capturing intricate data patterns and dependencies.

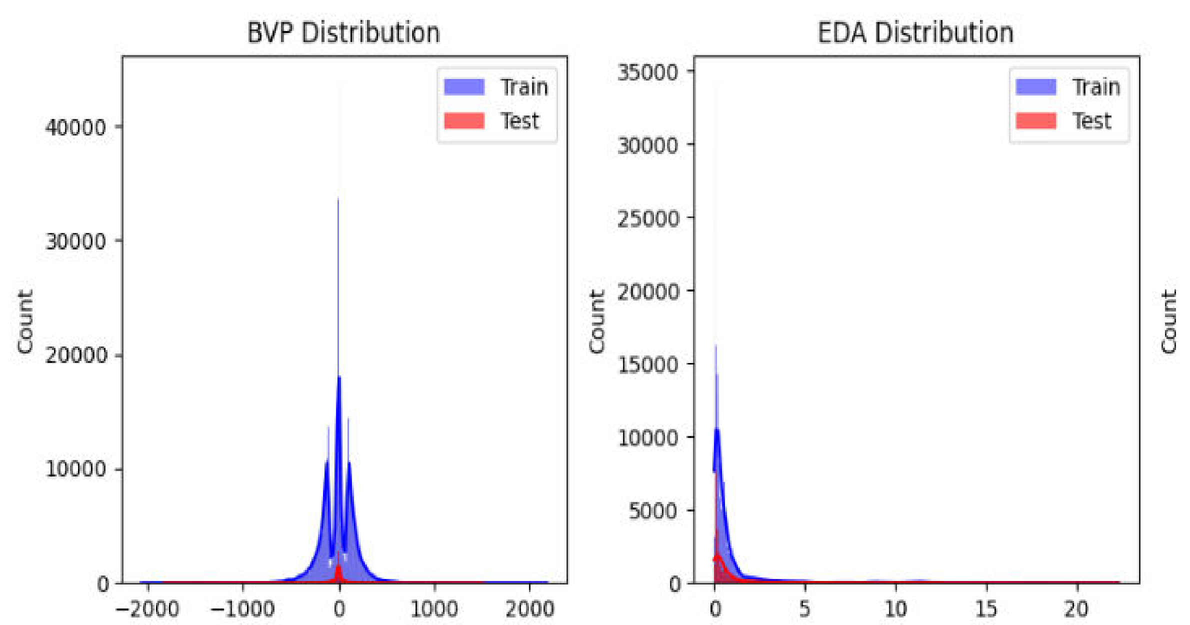
By processing sequences on a dataset, the model improves its accuracy in stress level classification. This advanced approach has applications. Deepens our understanding of stress dynamics, for effective management.

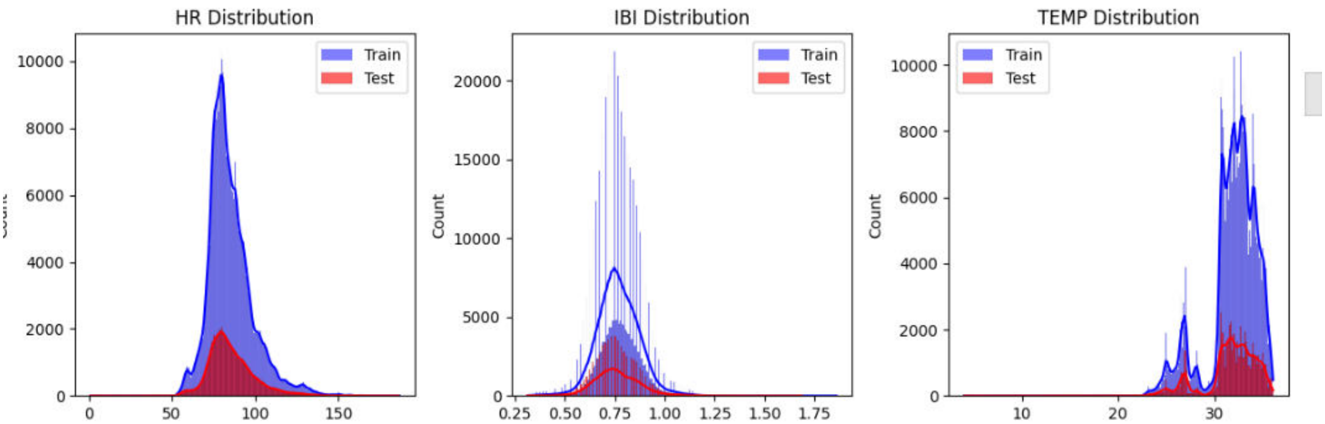
3.2 PROPOSED ARCHITECTURE

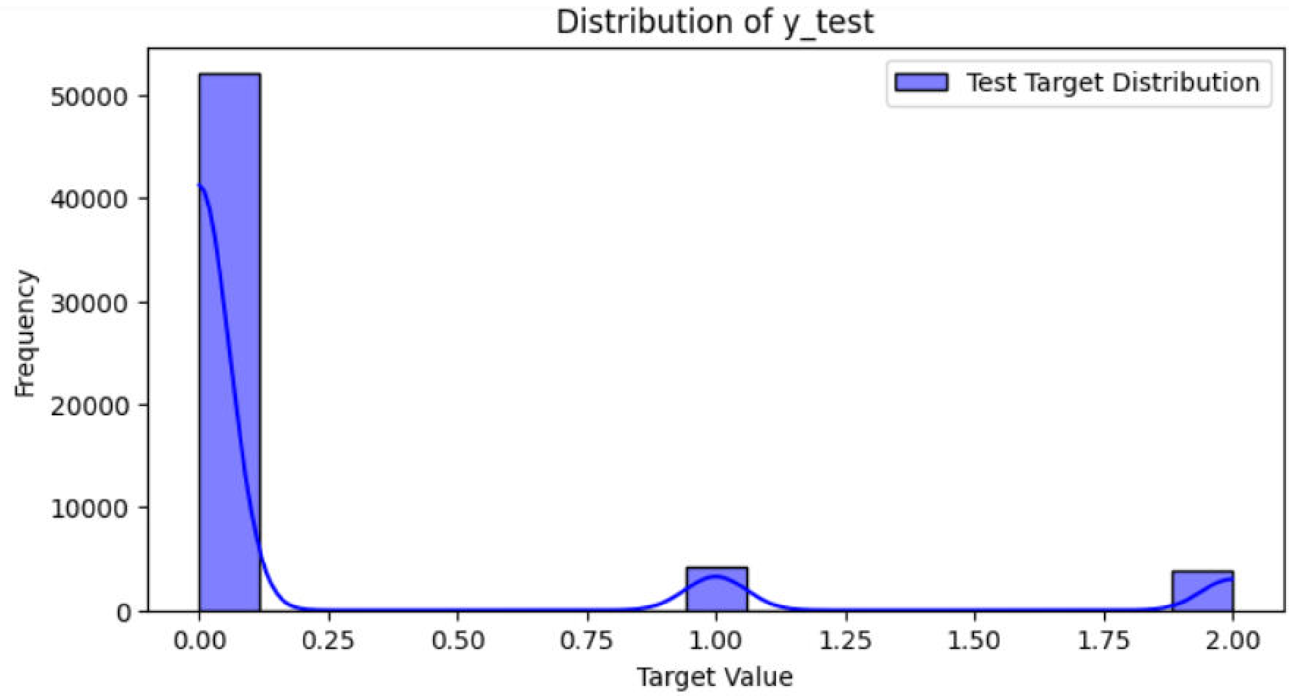


4.RESULTS AND DISCUSSION

VISUALIZATION







FINAL RESULT :

```
# Train the model
batch_size = 64
epochs = 2

stats=model.fit(X_train, y_train, batch_size=batch_size, epochs=epochs , validation_split=0.2)
```

```
Epoch 1/2
7823/7823 [==============================] - 894s 114ms/step - loss: 0.0410 - accuracy: 0.9894 - val_loss: 0.0197 - val_accuracy: 1.0000
Epoch 2/2
7823/7823 [==============================] - 893s 114ms/step - loss: 0.0244 - accuracy: 0.9935 - val_loss: 0.0044 - val_accuracy: 1.0000
```

5.CONCLUSION

Our study used Bidirectional Long Short Term Memory (Bi LSTM) networks, a sort of network design, to assess sensor data and monitor stress levels. We thoroughly examined the performance of the Bi LSTM model by comparing it to research conducted in the field. In addition, we looked at how alternative design decisions and hyperparameter configurations affected the model's findings, which provided insights into how to improve its effectiveness. Our findings illustrate the benefits of using network techniques instead of typical machine learning methods for this purpose. We had a 99% accuracy rate in categorizing stress levels. These strong results pave the path for applications in stress monitoring and diagnostics.

REFERENCES

- Von Rosenberg, Wilhelm, et al. "Resolving ambiguities in the LF/HFratio:

LF-HF scatter plots for the categorization of mental and physical stress from HRV." Frontiers in physiology 8 (2017): 360.

- Ishaque, Syem, Naimul Khan, and Sri Krishnan. "Trends in heart-rate variability signal analysis." Frontiers in Digital Health 3(2021):639444.

- Giordano, Frank J. "Oxygen, oxidative stress, hypoxia, and heart failure." The Journal of clinical investigation 115.3 (2005): 500-508.

- Zhou, Lufang, et al. "Effects of regional mitochondrial depolarization on electrical propagation: implications for arrhythmogenesis." Circulation: Arrhythmia and Electrophysiology 7.1 (2014): 143-151.

- Terman, Alexei, and Ulf T. Brunk. "The aging myocardium: roles of mitochondrial damage and lysosomal degradation." Heart, Lungand Circulation 14.2 (2005): 107-114.

- Saadeh, Khalil, and Ibrahim Talal Fazmin. "Mitochondrial dysfunction increases arrhythmic triggers and substrates; potential
- anti-arrhythmic pharmacological targets." Frontiers in Cardio vascular Medicine 8 (2021): 646932.

- Balsam, Paweł, et al. "Study design and rationale for biomedical shirt based electrocardiography monitoring in relevant clinical situations: ECG-shirt study." Cardiology Journal 25.1 (2018): 52-59.

- Desai, Chintan S., et al. "Electrocardiographic abnormalities and coronary artery calcium for coronary heart disease prediction and reclassification: The Multi-Ethnic Study of Atherosclerosis(MESA)." American heart journal 168.3 (2014): 391-397.

- Zhang, Weiwei, et al. "Partial directed coherence based graph convolutional neural networks for driving fatigue detection." Reviewof Scientific Instruments 91.7 (2020).

- Deng, Ping-Yu, et al. "Detecting fatigue status of pilots based on deeplearning network using EEG signals." IEEE TransactionsonCognitive and Developmental Systems 13.3 (2020): 575-585.

- Ahmadi, Amirmasoud, Hanieh Baz regarzadeh, and KamranKazemi."Automated detection of driver fatigue from electro encephalo graphy through wavelet-based connectivity." Biocybernetics and Biomedical Engineering 41.1 (2021): 316-332.

- Chen, Chunxiao, et al. "EEG-based detection and evaluation of fatigue caused by watching 3DTV." Displays 34.2 (2013):

- Monteiro, Thiago Gabriel, et al. "Investigating an integrated sensor fusion system for mental fatigue assessment for demanding mari time operations." Sensors 20.9 (2020): 2588.

Author's Profiles

E-mail (venugopal@nriit.edu.in)

PALLAGANI VENU GOPAL Working as an Associate Professor of the CSE (Data Science) Department of NRI INSTITUTE OF TECHNOLOGY. Boasting over 16+ Years of rich experience in engineering academics. He has successfully taught a spectrum of undergraduate and postgraduate courses while also mentoring numerous B.Tech., M.Tech. Projects. Interested Research areas are the Internet of Things, Machine Learning, and Image Processing.

E-mail (k.anu7422@gmail.com)

Currently, **KUNDETI ANURADHA** is pursuing a Bachelor's degree in Computer Science and Engineering with a concentration in Data Science at the NRI Institute of Technology. She completed a mini-project, "Waiter tip prediction using machine learning," demonstrating his considerable proficiency with machine learning. Exhibiting his commitment to career progress and ongoing learning, his certifications include Python for Data Science and Black Bucks Internship – Black Bucks Pvt LTD. He also has certifications from NPTEL courses in cloud computing and The Joy of Computing UsingPython.

E-mail(vaddisaimani834@gmail.com)

VADDI SAI MANIKANTA is currently enrolled in the B.Tech program in Computer Science and Engineering with a specialization in Data Science at NRI Institute of Technology. He has successfully completed a mini-project "Electricity price prediction", of artificial intelligence & machine earning. He has completed a noteworthy internship with Blackbucks company, gaining valuable industry Underscoring his commitment to continuous learning and professional development. He had an Industrial Internship Certification in full stack programming using Java.

E-mail (nareshkaja996@gmail.com)

KAJA NARESH BABU Science and Engineering with a specialization Data Science at NRI Institute of Technology. He has successfully completed a mini-project "Image classification using cnn" of artificial intelligence & machine learning. He has completed a noteworthy internship with Blackbucks company, gaining valuable industry experience. underscoring his commitment to continuous learning and professional development. He had an Industrial Internship Certification on full stack programming using Java. Nptel certification with cloud computing and udemy with data visualisation with tableau and python.

E-Mail(Vukantidivyatejasai@gmail.com)

VUKANTI DIVYA TEJA SAI Science and Engineering with a specialization Data Science at NRI Institute of Technology. He has successfully completed a mini-project "Electricity price prediction " analysis using machine learning artificial intelligence. He has completed a noteworthy internship with Blackbucks company, gaining valuable industry experience. underscoring his commitment to continuous learning and professional development. He had an Industrial Internship Certification on full stack programming using Java. Nptel certification with cloud computing and udemy with data visualisation with tableau and python.