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# Facial Feature-Based Drowsiness Detection With Multi-Scale Convolutional Neural Network

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**Abstract:** This project aims to solve the important problem of reducing crashes caused by drivers who are sleepy, which is very dangerous for road safety, people's lives, and property. The study uses deep learning methods, especially the Multi-Scale Convolutional Neural Network (MCNN), to correctly find and tell the difference between driving while sleepy and while awake. Even though technology has improved, it is still hard to tell when someone is sleepy. This means that strong tracking methods are needed to keep accidents from happening. The study stresses how important it is to use good datasets like NTHU-DDD and YAWDD to test and train the suggested MCNN framework. The project also looks into other neural network designs, like DenseNet and Xception, as well as group methods, like Voting Classifier and Stacking Classifier, to make the system work better. These researchers are trying to get accuracy levels above 99% by using a wide range of machine learning models and ensemble methods. This will help make the roads safer and lower the number of accidents caused by drivers who aren't paying attention.

*Index Terms: Accuracy, drowsiness, deep learning, feature extraction, optimization, pre-processing*

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## 1. INTRODUCTION

The rise in car crashes over the past few years has become a major world issue, with major effects on public health and safety. As more people get cars, more people are living in cities, and more people have access to cars, which has made car crashes more common and worse [1]. Notably, car crashes are the top cause of death for people aged 15 to 49 around the world, which shows how important it is to solve this problem right away [1].

In this situation, India, like many other countries, has to deal with the difficult task of managing road safety. One shocking 1.3 lakh car crashes happened in India in 2020, hurting more than 3.4 lakh people [2]. Even though these numbers are scary, the number of deaths from car crashes has gone down significantly in 2020. This is due to a number of things, including better traffic management, stricter regulation of the new Motor Vehicle Act, and the COVID-19 lockdown measures [2]. The drop in car accidents, injuries, and deaths shows that safety measures are working, but it also shows that we need to stay alert and come up with new ways to lower risks even more.

Further analysis of the data shows that the trends are not the same in all of India's states and union territories (UTs). For example, the number of car crashes has gone down by 18.5% total from 2019 to 2020, but the rates of injuries and deaths are different in different areas [3]. Some states, like Tamil Nadu, Uttar Pradesh, and Maharashtra, have high accident rates that need specific solutions and plans made for each area [3].

One of the scary things about the rise in crashes is that drivers are getting sleepy. Drivers can become sleepy for a number of reasons, such as not getting enough sleep, drinking alcohol, being stressed, or taking medicine [4, 5]. Drunk driving can have very bad results, putting not only the lives of drivers in danger but also the lives of passengers, walkers, and other people on the road [6]. Because experts know how important it is to find and prevent crashes caused by drowsiness, they have been working on making effective screening methods.

In the past, drowsiness identification was done by watching how people drive, studying bodily signs, and keeping an eye on readings taken by vehicles [7]. Video processing methods are becoming a good way to check how a driver is acting because they can pick up on small signs like eye movements, breathing, and changes in head position [8]. By collecting and studying camera data, researchers can learn how sleepy drivers are and take action to stop crashes before they happen.

Detecting drowsiness has relied on facial feature recognition, which uses the small changes in facial expressions and movements that happen when someone is tired [13]. By looking at movements, changes in behavior, and weakened reflexes, experts can figure out when drivers are feeling sleepy and take the right steps [14]. Also, machine learning (ML) methods have been widely used to find people who are sleepy, using big data sets to teach classification models [16]. The usefulness of machine learning-based methods depends on having large datasets and being able to correctly guess and analyze oddities [17]. This study aims to add to the current work in managing road safety by focusing on finding and stopping crashes that happen because of a driver being sleepy. The study aims to create strong sleepiness detection models that can correctly judge a driver's behavior in real-life situations by using advances in deep learning and video processing. The study's goal is to make sleep recognition systems work better by looking at face traits, driving habits, and bodily cues. This should lead to fewer car crashes.

To sum up, tackling the complicated problem of road safety needs a diverse approach that includes new technologies, changes to policies, and changes in how people act. By using improvements in machine learning, data analytics, and video processing, academics and lawmakers can work to make roads safer and stop people and property from being lost needlessly. This study is an important step toward reaching this goal, and it could have a big impact on efforts to improve road safety around the world.

## 2. LITERATURE SURVEY

In the past few years, driver sleepiness recognition has gotten a lot of attention because it is so important for road safety. To make sleep monitoring systems that work well, researchers have looked into a number of different methods, such as deep learning, picture processing, and bodily signal analysis. The goal of this literature review is to give an outline of the most important studies in this area, focusing on the methods, techniques, and results that were found by various experts.

Deep learning methods have become useful for finding sleepy drivers because they can pull out complex traits from large amounts of data. A group of researchers led by Khan et al. suggested using a single deep learning system with multiple scale detectors to find geospatial objects in high-resolution satellite images [4]. Multi-scale detectors were originally designed to find objects, but their ideas can be used to find people who are sleepy, since it's important to pick up on minor cues like changes in behavior and facial expressions.

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Magán et al. used deep learning on series of pictures to find drivers who were falling asleep at the wheel, and the results looked good in real-time tracking situations [9]. Their work shows that deep learning can be used to look at trends in time and tell if someone is sleepy by watching how their visual cues change over time.

A lot of research has been done on both deep learning and picture processing methods for finding people who are sleepy. Moujahid et al. suggested a quick and small face description that is perfect for finding sleepy drivers [10]. Their method is a simple but effective way to watch people in real time by focusing on face traits that show signs of tiredness. Also, Chaabene et al. used convolutional neural networks (CNNs) to look at electroencephalogram (EEG) signals to find people who were sleepy. This shows how physiological signal analysis can be used to help visual cues [11]. Their study stresses how important it is to use more than one method to fully spot drowsiness.

Combining deep learning with bodily signal analysis has also shown promise in finding people who are sleepy. Quddus et al. suggested a model that combines long short-term memory (LSTM) and CNNs to find drivers who are falling asleep [12]. Their model was better at finding drowsiness in EEG readings by using the time patterns caught by LSTM and the spatial features retrieved by CNNs. In the same way, Balam et al. created an automatic classification method for detecting sleepiness using CNNs and EEG data [20]. Their work shows how EEG-based methods could be used to get real-time information about how sleepy a driver is.

Also, experts have looked into small and easy-to-understand models for finding drivers who aren't paying attention, trying to find a mix between accuracy and speed. A small CNN design was suggested by Cui et al. as a way to find driver tiredness across subjects using single-channel EEG data [23]. Their model can be understood while still showing good results, so it can be used in a variety of real-world situations. Rajamohana et al. used a mix of CNNs and bidirectional LSTM networks to find drivers who were falling asleep [32]. By using the best parts of both designs, they were able to make their model work well in real-life situations.

Overall, the literature review shows the variety of ways and methods used to find drivers who aren't paying attention. Deep learning methods, like CNNs and LSTM networks, have shown a lot of promise in the ability to find complex trends in bodily and visual data. Image processing systems that are designed to identify and analyze face features have also shown promise in finding minor signs of sleepiness. In addition, using more than one method, like EEG data, makes sleep monitoring systems more reliable and useful. Going forward, more study is needed to look into mixed methods and how these systems can be used in the real world to improve road safety.

## 3. METHODOLOGY

**a) Proposed Work:**

The suggested work presents a unique Multi-Scale Convolutional Neural Network (MCNN) structure that is designed to correctly identify cases of driver sleepiness. The system gets important data for a complete study from the YAWDD and NTHU-DDD files, which are made up of video clips of drivers at work. This dataset collection makes it easier to train and test the classification model, which makes sure that drowsiness can be accurately detected in a wide range of driving situations and behaviors that are recorded in these datasets. The suggested MCNN framework aims to get very good at finding and classifying drowsiness in real-time driving situations

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by using the wide range of driving situations and behaviors shown in these datasets. This method could help make the roads safer by sending quick tips and taking action to stop crashes caused by drivers who aren't paying attention.

**b) System Architecture:**

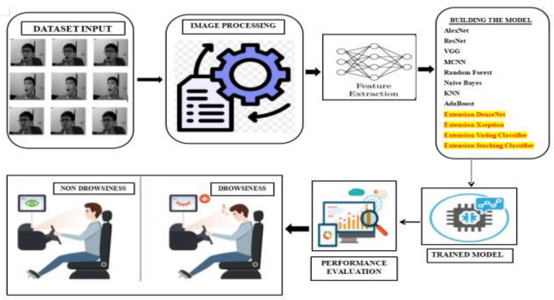


Fig 1 Proposed Architecture

Several important parts make up the system design for detecting sleepiness in drivers. Video patterns from datasets like YAWDD and NTHU-DDD are first put in, which sets the stage for training the model. Following image processing to find features that show signs of sleep, these movies go through feature extraction to turn the preprocessed data into a format that can be used for training the model. During the model building process, different algorithms are used, including AlexNet, ResNet, VGG, MCNN, Random Forest, Naive Bayes, KNN, and AdaBoost. These algorithms are trained on the collected features to make strong predictors. Lastly, the learned models are put through a performance test to see how well and how accurately they can tell the difference between sleepy and awake states. This organized method guarantees the creation of a complete sleepiness detection system that can raise traffic safety by correctly detecting instances of drivers being sleepy.

**c) Dataset:**

**NTHU-DDD:** The NTHU-DDD dataset is an important source because it includes long video records that show different driving habits in different situations. These records provide a large collection of information about the actions, facial expressions, and external factors that can be used to identify sleep. Researchers can learn a lot about how sleep affects driving in real life by using the NTHU-DDD dataset.

Fig 2 Non Drowsy Dataset

**YAWDD:** The YAWDD dataset adds to the NTHU-DDD dataset by including more video clips that show how people drive. These extra videos add to the dataset by showing a wider range of driving situations and actions. This makes the dataset more diverse and accurate. Adding data from the YAWDD dataset to the sleep detection model lets it learn from more situations, which makes it more reliable and able to handle different driving conditions. Together, the NTHU-DDD and YAWDD files provide a complete base for training and testing the sleep detection system. This helps make progress in study into road safety and efforts to stop accidents.

Fig 3 Drowsy Dataset

**d) Image Processing:**

*Re-scaling the Image:* To re-scale a picture, you change the numbers of the pixels to a range you want, usually between 0 and 1 or -1 and 1. By making sure that the input data is within a reasonable range of numbers, this step of standardization speeds up the convergence process during model training. By rescaling the picture, we make sure that the intensity levels are the same across all photos in the collection. This lowers the variation and makes sure that the model always acts the same way across samples.

*Shear Transformation:* This type of transformation changes the shape of a picture by moving a part of it along a straight line. This method for adding to the dataset helps make it more diverse by modeling how picture views and orientations change in the real world. We make changes to the dataset using shear transformation so that the model can work better with new data and reliably spot drowsiness in a variety of driving situations.

*Zooming the Image:* Changing the size of the picture by zooming means adding or removing pixels. This method for adding details helps the model learn how to show drowsiness in a way that doesn't change based on the image's size or quality. By zooming in on the picture, we mimic changes in viewing distances or camera resolutions. This makes sure that the model can correctly spot sleepiness in a range of situations.

*Horizontal Flip:* By flipping the picture along its vertical line, horizontal flipping makes a mirror copy of the original. This method adds to the complexity of the information by adding different object positions and views. By using pictures that have been flipped horizontally, the model learns to spot drowsiness from a variety of angles. This makes it more resistant to changes in driver positions or camera angles.

*Reshaping the Image:* If you want to reshape a picture, you have to change its measurements so that they work with a certain neural network design or processing need. This step before handling the dataset makes sure that all the pictures have the same size, which makes training and inferring models easier. By changing the shape of the picture, we get it ready for more processing, like convolutional operations or feature extraction, and make sure it works with the network design that was chosen.

**Feature extraction**

*Reading the Image:* Getting the picture data from the information.

*Resizing the Image:* When you resize a picture, you change its measurements to a size that is needed for further processing.

*Convert the Color:*To standardize processing, you may need to change the image's color scheme, such as from RGB to grayscale.

*Appending the Image and Labels:* Putting together the processed picture data with the labels or goal values that go with them makes supervised learning easier.

*Conversion to NumPy value:* Changing the information into NumPy arrays so that it can be used more efficiently for math operations and editing.

*Label Encoding:* Turning classification data into number names so that the model can understand and work with these groups while it is being trained.

These steps for processing images are necessary to get the dataset ready and pull out useful features that can be used to train machine learning models well.

**e) Algorithms:**

**AlexNet:** AlexNet is a deep convolutional neural network framework made to sort images into different groups. AlexNet could be used in this project to pull out features from pictures of faces recorded in driving videos. Its deep design lets it pick up on complicated patterns and features in face pictures, which can then be used to tell if someone is sleepy.

**ResNet:** ResNet, which stands for "Residual Network," is a deep learning design loved for its residual learning structure. ResNet could be used to get features for the sleep detection project because it can deal with problems where gradients disappear in very deep networks. Its leftover blocks make it possible to train very deep networks, which could help with recording face traits that aren't simple.

**VGG:**VGG is another deep convolutional neural network design. VGG stands for "Visual Geometry Group." VGG is known for being easy to use and having a consistent structure made up of many convolutional layers. It could be used in this project to pull features from face pictures, which would be an easy and accurate way to find people who are sleepy.

**MCNN:** MCNN is the main model used in the project to find people who are sleepy. This program is especially made to look at face traits taken from driving videos. MCNN uses many convolutional layers that work at different sizes. This lets it get both fine and coarse data from face pictures.

**Random Forest:** Based on decision trees, Random Forest is a well-known ensemble learning method. Random Forest could be used in the project as part of ensemble methods to combine results from different models. This could make the total accuracy of detecting sleepiness better.

**Naive Bayes:**This is a statistical predictor called Naive Bayes. It is based on Bayes' theorem and the idea that traits are independent of each other. It's not usually used for picture classification jobs like finding people who are sleepy, but it might work for other traits or information related to the driving data.

**KNN (K-Nearest Neighbors):**The KNN (K-Nearest Neighbors) method is a simple and easy-to-understand way to sort data by finding the points that are closest to a given data point. KNN could be used for classification tasks in this project as long as the collected face features are shown as vectors in a feature space.

**AdaBoost:**AdaBoost is a type of ensemble learning that takes several weak models and builds a strong one from them. A lot like Random Forest, AdaBoost can be used as part of ensemble methods to make sleepiness recognition more accurate overall.

**DenseNet:**DenseNet is a shape of a convolutional neural network that is known for having layers that are very closely related to each other. As the project goes on, DenseNet could be used for feature extraction, taking advantage of its ability to pick up complex features across multiple network levels.

**Xception:** You can add to the Inception design with Xception, which is known for its depthwise separable convolutions. Xception could be used for feature extraction in the project update. This could make it more efficient and faster than standard designs.

**Voting Classifier (RF+DT):**The Voting Classifier (RF+DT) is a type of ensemble learning that takes the results of several base classifiers and adds them up. As an addition, the Voting Classifier could be used with Random Forest and Decision Trees as base classifiers to make the total accuracy of detecting sleepiness better.

**Stacking Classifier (RF+MLP+LightGBM):**The Stacking Classifier (RF+MLP+LightGBM) is another type of ensemble learning that uses more than one classifier and learns to mix their results. To make the project even better, the Stacking Classifier could be combined with the Random Forest, Multi-layer Perceptron (MLP), and LightGBM classifiers to make model stacking even more accurate at finding sleep.

**4. EXPERIMENTAL RESULTS**

**Accuracy:** How well a test can tell the difference between sick and healthy people is called its accuracy. To get an idea of how accurate a test is, we should figure out what percentage of cases are true positives and true negatives. In terms of math, this can be written as

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

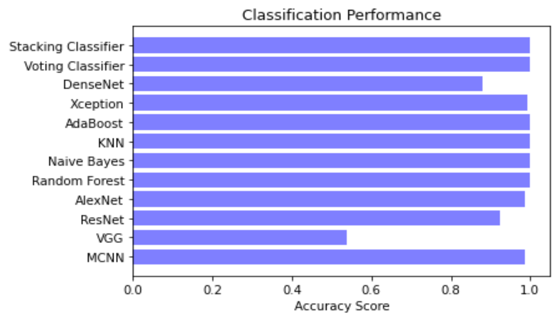


Fig 4 Accuracy Comparison Graphs

**F1-Score:** There is a machine learning rating tool called the F1 score that measures how accurate a model is. It adds up the accuracy and review scores of a model. The accuracy measurement figures out how often, across the whole collection, a model correctly predicted what would happen.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

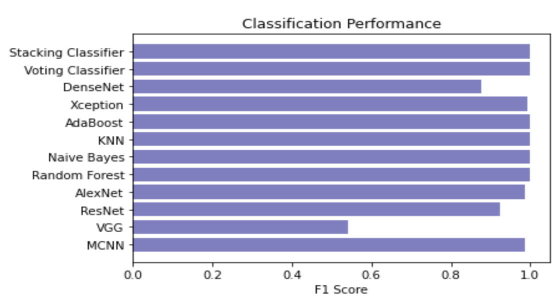


Fig 5 F1 Score Comparison Graphs

**Precision:** Precision is the percentage of correctly classified events or samples that are among the hits. So, the following method can be used to figure out the accuracy:

Precision = True positives/ (True positives + False positives) = TP/ (TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

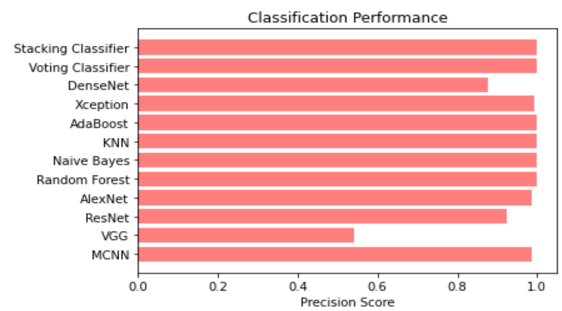


Fig 6 Precision Comparison Graphs

**Recall:** Recall is a machine learning variable that measures how well a model can recognize all relevant examples of a certain class. It's the percentage of expected positive feelings that turn out to be real positive feelings. This tells us how well a model can catch instances of a certain class.

$$Recall = \frac{TP}{TP + FN}$$

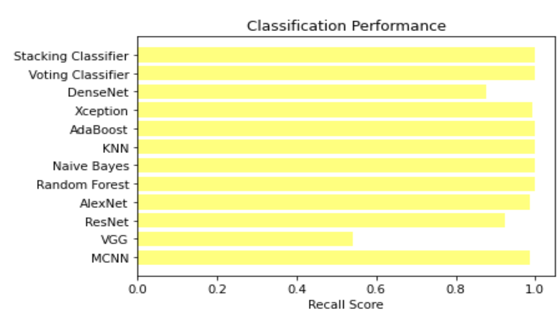


Fig 7 Recall Comparison Graphs

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| ML Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| MCNN | 0.987 | 0.987 | 0.987 | 0.987 |
| VGG | 0.539 | 0.541 | 0.541 | 0.541 |
| ResNet | 0.923 | 0.924 | 0.924 | 0.924 |
| AlexNet | 0.987 | 0.987 | 0.987 | 0.987 |
| Random Forest | 1.000 | 1.000 | 1.000 | 1.000 |
| Naive Bayes | 1.000 | 1.000 | 1.000 | 1.000 |
| KNN | 1.000 | 1.000 | 1.000 | 1.000 |
| AdaBoost | 1.000 | 1.000 | 1.000 | 1.000 |
| Extension Xception | 0.993 | 0.993 | 0.993 | 0.993 |
| Extension DenseNet | 0.879 | 0.878 | 0.878 | 0.878 |
| Extension Voting Classifier | 1.000 | 1.000 | 1.000 | 1.000 |
| Extension Stacking Classifier | 1.000 | 1.000 | 1.000 | 1.000 |

Fig 8 Performance Evaluation Table

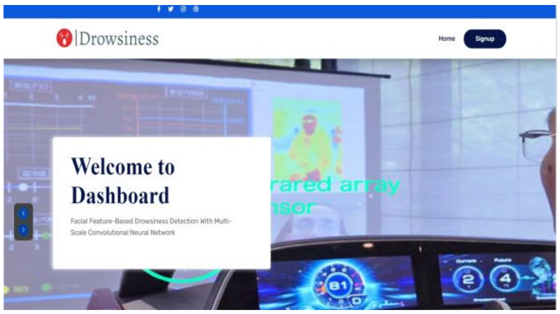


Fig 9 Home Page

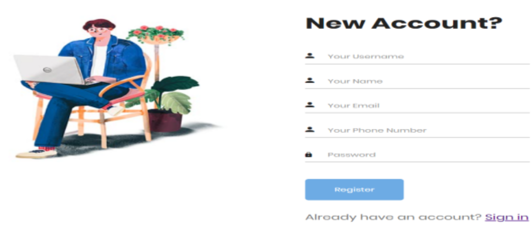


Fig 10 Registration Page

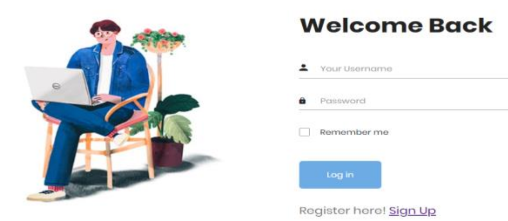


Fig 11 Login Page

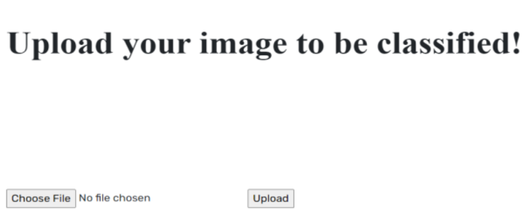


Fig 12 Upload Input Image

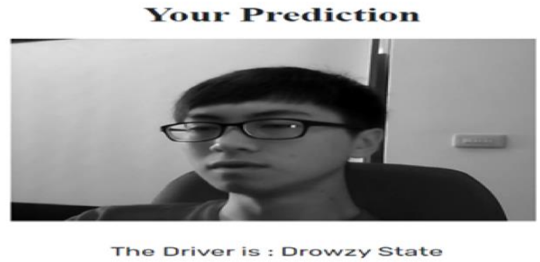


Fig 13 Predicted Results

## 5. CONCLUSION

In conclusion, using the MCNN framework to create an accurate sleep detection model is a big step toward making the roads safer by telling the difference between drivers who are drowsy and those who are not. By breaking up video clips into frames and pulling out face features, the model shows that it can spot signs of tiredness and let drivers know about them. Using the YAWDD and NTHU-DDD datasets makes sure that the model is strong and can be used in a wide range of driving situations. This results in amazing accuracy rates of over 98%.

The MCNN model's performance review also shows that it works better than traditional methods, which shows that it could be used in the real world to stop crashes caused by drivers who aren't paying attention. Adding ensemble methods and advanced deep learning models to the project makes it even more accurate and reliable, showing a dedication to always getting better.

## 6. FUTURE SCOPE

Looking ahead, there are a number of ways that the sleep recognition model could be explored and improved in the future. One possible step in the right direction is to add real-time tracking features that would let drivers know right away if they see signs of being sleepy. More study could also be done to make the model's computations more efficient so that it can be used in places with limited resources, like integrated systems in cars.

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Also, adding mixed data sources like bodily signs and car tracking data could help us understand driver sleepiness better and make the model more accurate. Efforts to make the model easier to understand and explain would also help build trust and acceptance among partners and end users. Research and development must continue in order for sleepiness recognition systems to become more useful and effective in keeping people safe on the roads.

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**Dataset used:**

**https://www.kaggle.com/datasets/banudeep/nthuddd2**