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Personalized and Real-Time Adaptive Headlight System using Deep Learning and IoT for Optimal Visibility

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***Abstract*—The automobile industry is one of the primary factors in world mobility that facilitates efficient transportation of people and goods, thus contributing toward economic growth. However, road accidents, especially at night, are still one of the most serious issues-mainly caused by poor visibility. Such a condition, in most cases, results from bright glare from opposing directions and adverse weather conditions. We are introducing a real-time, personalized adaptive headlight system in an effort to control such risks. This system varies the brightness of the headlights according to factors such as the approach of oncoming vehicles, dominating weather conditions, and the comfort level of the driver. Sensors and IoT components run these factors by employing deep learning algorithms to collect continuous feedback from drivers for the optimization of visibility. This adaptive headlight system aims at improving safety and comfort with a substantial reduction in the accidents that occur at nighttime by integrating this novelty of cutting-edge technologies with driver inputs.**

***Index Terms*—FCNN (Fully Connected Neural Network),Headlight Optimization, Deep Learning, Driver Characteristics, Vehicle Features, Light Intensity Classification, Data Preprocessing, Predictive Modelling, Automotive Safety, Real-Time Automation.**

I. INTRODUCTION

With the rapid advancement of automobile technology, finding ways to improve driver safety during tough road conditions has become one of the priority topics for discussion in research. Headlights are one of the most important components of automobiles because they help improve safety while driving, especially at night or in low visibility settings, and so have always provided static illumination, which could not change with time and varied circumstances. These systems adapt the brightness of the headlights in response to a road curvature or ambient light levels, but are generally not customized; therefore, their value to the user with distinct visual needs, driving habits, and vehicle conditions is diminished.

This paper describes a Personalized and Real-Time Adaptive Headlight System developed using state-of-the-art DL techniques and IoT technology and supplies fully adapted lighting experiences. It involves making contextually informed quick adjustments in terms of LED headlight intensity with the help of a Fully Connected Neural Network model that has been trained on hefty sensor data, captured through an IoT framework. For capturing real-time ambient light levels, an IoT network of LDRs is employed with the Arduino ESP8266 module for capture and wireless data transfer. Information is transferred to a cloud infrastructure hosted on the Adafruit platform, which processes and stores the data. Continuous monitoring and analysis help make realtime

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decisions possible. The experience should be personalized. Hence, factors specific to drivers such as height, experience, vision quality-for instance, the use of corrective lenses-and driving focus are taken into consideration. Parameters specific to vehicles include ground clearance and windshield condition.

These parameters allow the model to self-adjust in ways that are responsive not only to external lighting conditions but also to the needs of each driver and specific vehicle. It is trained on a global scale, thus making it generalizable across regions which differ in infrastructure, variations of lighting, and road environment. It makes use of real-time feedback loops via IoT for this purpose. It accordingly sends the altered settings to the car based on the intensity advised by the predictive model developed. Therefore, within a short span of time, the recommended intensity automatically finds its way into the LED headlights.

The mechanism of feedback provides a smooth adaptation scenario for lighting to drivers. Improving the driver's sight at the same time, minimizes glare for other approaching vehicles. The system could learn and improve itself over time using the storage and processing facilities available in Adafruit cloud this is by acquiring new data from different settings while improving the model accuracy through constant feedback. This adaptive headlamp system represents a next-generation data-driven solution combined with DL and IoT to upgrade comfort and safety in various driving scenarios. It is a very useful addition to the intelligent vehicle systems around the globe because it makes drivers have better light sight while simultaneously lowering their possibilities of accidents through tailored real-time adjustments.

II. Literature Survey

Gnanasekaran T, Senthil Kumar K R and Bharath Singh Jebaraj [1]: An important vehicle safety monitoring system, the paper follows various crucial health indicators, such as heart rate and blood alcohol content level, to enhance road safety. It also enhances headlight intensity based on oncoming vehicles to minimize glares. Nonetheless, the system does nothing to check driver fatigue and distractions. Challenges in real-time data processing and compatibility with available car technologies work against it.[1]

Jacob Kwaku Nkrumah, Yingfeng Cai, Ammar Jafaripournimchahi, HaiWang &Akolbire Atindana [2]: The Arduino-based automatic headlight beam management system focuses on managing nighttime accidents through controlling headlight brightness with regard to glare. Nevertheless, it does not incorporate driver health monitoring; hence it cannot control any potential impairment. A radar sensor in the system can only detect an object within a limited range; therefore, its adaptability to various driving conditions is quite restricted. Another deficiency of this system is that it does not comprise real-time health data of the driver, minimizing its effectiveness toward complete safety.[2]

Basma Al-Subhi, Feras N. Hasoon, Hilal A. Fadhil, Suresh Manic, Roshima Biju [3**]:** The LDR sensor and ultrasonic sensor-based Arduino smart car headlight control system adjusts the headlight intensity, according to ambient light and approach of the car during nighttime to ensure increased safety. It is not too expensive and adaptable to different lighting conditions. It lacks glaresensitive adjustments and health monitoring features. The proposed system used is not that robust when dynamic road conditions are considered because it has fewer processing speeds and capabilities; moreover, it relies on basic sensors compared to other developed solutions.[3]

Jan Vrabel, Ondrej Stopka, Jozef Palo, Maria Stopkova, Paweł Droździel and Martin Michalsky [4]: This study evaluates the range of visibility of dipped headlights along different road conditions with performance variations between different models, not incorporating realtime adaptation and health monitoring, which are key aspects of your system approach to improve safety through headlight adjustment in accordance with the driver's condition and environmental settings.[4]

Nannan Wang[5]: It adjusts headlight brightness with real-time sensor data, thus increasing brightness where needed for higher visibility and safety. It does not provide personalized driver feed-back and adapts to harsh weather and oncoming vehicle proximity. A much more personalized system may increase safety and comfort further by taking into consideration these factors.[5]

III. Proposed Model

A. Data Collection

The system collects data from various sources in order to vary the headlamp brightness by taking into account the environmental and vehicle-dependent variables.

Light Dependent Resistors (LDRs)

These sensors determine the degrees of ambient light in order to control the brightness of the headlights in different external illuminating conditions such as day, dusk, and night.

Fog Sensor
These sensors measure the fog or mist prevailing that diminishes visibility and needs an increase in headlamp brightness in order to make it safer while driving.

Environmental Sensors
Other sensors such as temperature and humidity are used to determine weather conditions like rain or fog. These help in precision adjustments of the headlamps.

Vehicle and Personalization Data
Vehicle Parameters: Information such as the ground clearance, headlamp designs, and speed of the vehicle is collected in order to know the best headlamp settings for that particular vehicle. Driver Preferences: The data about the driver, such as the years of driving experience, wearing corrective lenses, and personal preference with regard to lights, are accessed through a web interface. In this manner, the system becomes adaptive based on personal needs.

Dataset
The dataset for this study encompasses a comprehensive range of parameters that capture real-time driving conditions and personalized driver data, essential for developing an adaptive headlight system. It includes Height (Feet) and Driving Experience (Years), providing insights into the driver's physical attributes and expertise. The Vision Condition and Focus Level indicate the driver’s visual acuity and attentiveness, while Car Type and Ground Clearance offer context about the vehicle's characteristics. The Windshield Condition reflects clarity, impacting visibility, and the Headlight Type specifies whether the headlights are LED or another type, influencing light quality. Additionally, Low Beam Intensity (Lumens) and High Beam Intensity (Lumens) measure the brightness of the headlights, with PreAdjustment Intensity (Lumens) capturing the light output before any adjustments are made. The dataset also evaluates vehicle safety through Tire Condition, Brake Condition, and Steering & Suspension status, alongside driver wellness indicators such as Fatigue Level and Stress Level, which can affect driving performance. Reaction Time (seconds) is recorded to assess the driver’s responsiveness, while Weather Condition and Fog Condition describe external driving circumstances that influence safety. Rainfall (mm/h) quantifies precipitation intensity, and Light Intensity (Lux) measures ambient light levels, aiding in determining necessary headlight adjustments. By integrating these diverse parameters, the adaptive headlight system can make informed, real-time adjustments to enhance visibility and driving safety, effectively addressing the unique needs of each driver and the specific conditions encountered on the road.

B. Preprocessing Data

Data collected is subjected to preprocessing to extract key features and prepare it for model training in the algorithm of machine learning.

Missing Data
Missing data is either imputed or dropped to make the data complete.

Normalization
Normalization of continuous variables like light intensity, speed of the vehicle, temperature and humidity is done in the model so that no single feature dominates the model and balanced features are provided as input to the model.

One-Hot Encoding
One-hot encoding is done for categorical variables like type of vehicle, condition of weather, and road conditions. It will be converted into numerical values.

Data Augmentation
Since the size of the dataset is relatively small, synthetic data generation is used to simulate various environmental conditions, types of roads, and driving circumstances, thus helping in creating a more diversified and robust dataset for training purposes.

C. Model Training (Fully Connected Neural Network - FCNN)

The system utilizes a fully connected neural network (FCNN) for learning optimum headlamp intensity during optimum processed data inputs.

Feature Encoding
All these are fed into the FCNN model, through which it learned the appropriate light intensity it needs to emit.

D. Model Architecture

Input Layer
The input layer consists of the LDR values, weather conditions, the specification of the vehicle in the form of ground clearance and speed, and the preferences of the driver

Hidden Layers
This model has 3-4 layers of hidden layers with ReLU activation and neurons in each layer have fewer units than the preceding layer. 1. First hidden layer contains 128 neurons 2. Second one has 64 neurons 3.Third one holds 32 neurons.

Dropout Layers
Dropout layers with a dropout rate of 0.2–0.5 following each hidden layer stop overfitting and make generalization better.

Output Layer
This output layer contains six neurons that represent the classes for the intensities of light: Low, Medium- Low, Medium, Medium-High, High, and Extreme. A softmax activation function is used to produce a probability distribution across these classes.

Loss Function and Optimization
The categorical cross-entropy loss function is utilized in this scenario, given that it is a multi-class classification problem. The training uses Adam optimizer to perform dynamic adjustment of learning rates for better convergence and accuracy in models.

Model Evaluation
The trained model is evaluated against a test data set to evaluate the generalization capability and performance under unseen conditions.

E. Prediction and Real-Time Adjustment

After training, the model is used for real-time prediction of the correct headlamp intensity class with sensor data and user input.
Prediction: The model predicts one of six classes of light intensity:
Low: Clear daylight or perfect driving conditions
Medium-Low: The dusk or lightly dimmed conditions, such as overcast.
Medium: Clear nights with no loss of visibility.
Medium-High: Reduced visibility, such as light rain or slight fog.
High: Poor visibility, such as heavy rain, mist, or nighttime.
Extreme: Extremely poor visibility, such as intense fog or hazardous weather.

Real-Time Correction
The Nodemcu ESP8266 receives the expected intensity class and corrects LED headlights in real-time: Extreme: Brightened to their maximum capacity to achieve maximum visualization in highly low light conditions. Medium-High, High, Medium: Brighten the light to enhance brightness in low illumination. Medium-Low and Low: Dim the brightness when ambient conditions are bright. This dynamic control maintains maximum visibility and safety through the continuous changes in intensity based on the prevailing road and environmental conditions.

F. Frontend-Backend Interaction:

Flask Integration
A web interface built with Flask is where users can simply type in the vehicle's characteristics and preferences. The Flask backend will process this input data, interface the trained model, and establish predictions on real-time information.
Users can input vehicle details, such as car type and experience level, and adjust preferences like preferred headlamp brightness suited to their convenience.
The system combines such input with real-time sensor data to calculate the required headlamp brightness and the lights are adjusted automatically.

Visualization

On the web interface, the system shows the following Real-time sensor data, for example LDR values, weather conditions Predicted headlamp brightness class The adjustments applied to the LED headlamp. This would provide the user with more information on how the system has reached its decisions and increase the transparency as well as the control that the user exercises over the adjustments the adaptive headlamp system has made.

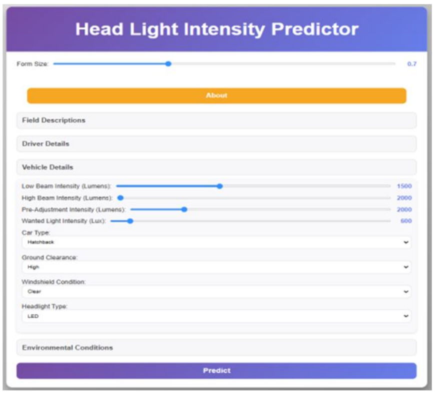

Fig.1 Frontend Visualization

G. IoT Components

Fig. 2 LDR Sensor

Fig. 3 Fog Sensor

Fig. 4 Nodemcu ESP 8266

Fig. 5 LED

The Nodemcu ESP 8266 system is responsible for:

Sensor data capture (e.g., LDR, fog sensor, environmental). Sends these data to the Adafruit IoT Cloud which is mirrored to the Flask backend for processing. Relies on the receptions of the predictions made by the model and changes LED headlights accordingly.

*Adafruit IoT Cloud:*The Adafruit IoT Cloud enables direct and interactive communication between the Nodemcu ESP8266 and the Flask backend to which the final predictions are relayed for reception by the Nodemcu ESP8266, which therefore changes the headlights.

Headlights Control by LED:

In the system, adjustment of the intensity of the LED headlights based on the predicted light intensity is made.*Low:* The brightness is minimum. *Medium Low:* Brightness is relatively low. *Medium:* Brightness is normal. *Medium High:* The brightness is increased.

High: The brightness is maximum for poor visibility.

Extreme: The brightness is full to deal with extremely low visibility conditions.

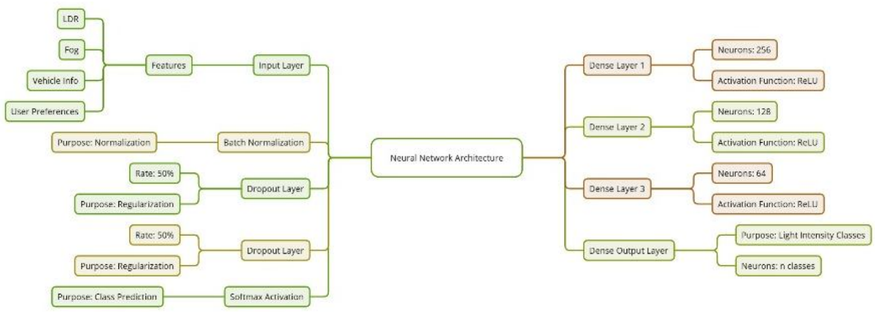

Fig. 6 Proposed Model Architecture

IV. RESULTS

The adaptive headlight prediction model achieved a high accuracy of **98.6%** on the test set, indicating strong performance in accurately classifying light intensity levels based on real-time driving conditions and driver-specific data.

A. Accuracy and Performance Metrics

With an overall accuracy of **98.6%**, the model demonstrates reliable performance in most real-world scenarios, as reflected in the high precision, recall, and F1 score metrics calculated for each light intensity class.

B. Precision

Each light intensity class showed precision values close to or above 0.98, indicating that the model rarely misclassified one intensity level as another.

C. Recall

The average recall across all classes was **0.98**, signifying that the model successfully identified most instances of each light intensity level.

D. F1 Score

The average F1 score was **0.98**, indicating a balanced performance across precision and recall for all classes.

E. Confusion Matrix

The confusion matrix provides a detailed breakdown of the model's classification performance for each class, in this matrix:
1. Diagonal values represent correct classifications.
2. Off-diagonal values indicate misclassifications, which are minimal across the matrix, supporting the model's high accuracy.

F. Model Accuracy Over Epochs

The accuracy curves for both the training and validation sets reveal a stable learning process:

G. Training Accuracy

Training accuracy increased over epochs, reaching close to 100%, which shows the model's capability to learn effectively from the training data.

H. Validation Accuracy

The validation accuracy also showed a steady upward trend, eventually stabilizing near the training accuracy, which indicates that the model can maintain high accuracy on new data without over fitting.

I. Precision, Recall, and F1 Score by Class

The model's performance metrics for each intensity class are as follows: These values show that all classes maintain high levels of precision, recall, and F1 score, underscoring the model's robustness and consistency across different light intensity levels.

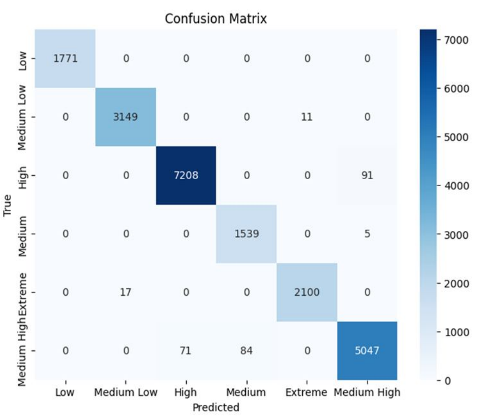

Fig. 7 Confusion Matrix

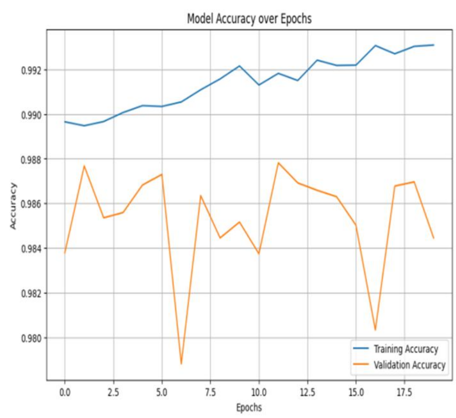

Fig. 8 Model Accuracy Over Epochs

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1771
1	1.00	0.99	0.99	3160
2	0.98	0.99	0.99	7299
3	0.96	1.00	0.98	1544
4	0.98	1.00	0.99	2117
5	0.99	0.96	0.97	5202
accuracy			0.98	21093
macro avg	0.98	0.99	0.99	21093
weighted avg	0.98	0.98	0.98	21093

Fig. 9 Classification Report

V. CONCLUSION

The adaptive headlight system achieved 98.6% accuracy, dynamically adjusting brightness based on personalized driver data and real-time conditions. Using a Fully Connected Neural Network (FCNN) with six intensity levels, it enhances visibility and safety, tailoring responses to each driver’s needs and environment. Stable metrics and high F1 scores confirm its robustness, while IoT integration enables seamless, real-time adjustments. This personalized approach has significant potential to improve road safety, especially in challenging visibility scenarios.

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