Detecting Sleepiness of The Driver Using Image Processing Technique

Mr. Pradeep V, Senior Assistant Professor, Department of Information Science and Engineering,
Alva's Institute of Engineering and Technology.
pradeepv@aiet.org.in
Namratha, Nisha Tellis, Shravya, Vshker Mayengbam
Department of Information Science and Engineering
Alva's Institute of Engineeing and Technology
Mangalore
Visvesvaraya Technological University,
Belgaum, Karnataka
namrataputhran5@gmail.com, tellisnisha@gmail.com,
shravyapoojary14@gmail.com, vshkermayengbam@gmail.com

***Abstract*—Most car accidents occur due to driver drowsiness, which is why we introduce a reliable and intelligent method for detecting it. Our method involves detecting eye closur techniques to accurately determine if the driver is feeling fatigued. To achieve this, we utilize a camera placed within the car to capture the driver's facial features. Initially, we use computer vision techniques to track and identify the face region within the captured video. We then extract the eye areas to analyze them for signs of drowsiness. By merging the results, we can detect the driver's state and send a warning message if necessary. Our experimental results validate the effectiveness of our approach.**

Keywords— Harr cascade, Sequential model

I. INTRODUCTION

Driver sleepiness is a serious issue that can cause accidents and fatalities on the road. Detecting driver sleepiness in real-time is therefore a critical task for ensuring road safety. Deep learning is a subfield or specialized area of machine learning that has shown remarkable performance in a variety of tasks such as image identification, speech identification, and natural language processing. Deep learning techniques can also be used to detect driver sleepiness from data collected through sensors and cameras in the car.

The objective of utilizing deep learning for driver sleepiness detection is to create an algorithm capable of analyzing data such as steering wheel movements, facial expressions, eye movements, and driving patterns, to evaluate the degree of driver alertness. Deep learning models can be trained on large datasets of labeled data to accurately predict the degree of driver sleepiness. in real-time.

One of the main reasons for vehicle accidents is driver fatigue, which poses a serious threat to people's lives and property security due to the frequency of these accidents. As per the National Highway Traffic Safety Administration (NHTSA), drowsy driving was responsible for an estimated 91,000 crashes, 50,000 injuries, and 795 fatalities in 2017 alone and 72,000 crashes, 44,000 injuries, and 800 fatalities in 2019 in the United States. The Global Status Report on Road Safety 2018, published by the World Health Organization (WHO) highlights that approximately 1.35 million individuals lose their lives due to road traffic crashes , and an additional 20-50 million people suffer non-fatal injuries, often resulting in long-term disabilities. Additionally, the report highlights that these deaths and injuries are largely preventable through effective road safety interventions, including measures to address driver fatigue and sleepiness.

In recent years, many endeavors have been made to create methods for detecting driver drowsiness in real-time. Three distinct methods for detecting drowsiness have been put forth, including approaches that rely on the driver's physiological signals, those that assess driver performance, and those that utilize image-based techniques.

The initial category of methods for detecting drowsiness focuses on physiological and non-visual symptoms that arise within the body due to drowsiness. To achieve this, electrodes are attached to various parts of the driver's body, such as the brain, muscles, and heart, in order to record the electrical activity. By analyzing the recorded data, the degree of drowsiness can be determined with reasonable accuracy. Nonetheless, these approaches are not suitable for practical applications due to their shortcomings, as they can be intrusive and cause discomfort to the driver.

The category of methods based on driver performance involves the installation of sensors in various parts of the vehicle, such as the steering and accelerator, as the first step. Subsequently, drowsiness detection process involves analyzing the signals obtained from these sensors and determining the vehicle's state. Although these methods exhibit a relatively high degree of accuracy,Their impracticality stems from their high cost. The third category of methods employs machine vision and image processing technologies to analyze a sequence of video frames capturing the driver's facial expressions, in order to determine whether the driver is drowsy or on the verge of falling asleep. When drowsy, drivers tend to nearly close their eyes and occasionally yawn, which are obvious facial expressions of drowsiness. As such, the methods based on facial features detection are highly visualized and easily comprehensible.

This paper uses a real-time method for detecting and warning against driver drowsiness, which relies on multiple facial features. This method aims to reduce the impact of light and glasses, to some extent.

II. RELATED WORKS

The initial approach relies on analyzing vehicle behaviors to assess the driver's condition. This technique primarily involves detecting and analyzing the movement of the vehicle, such as the steering wheel, acceleration pedal, braking, and lane keeping, to evaluate the driver's degree of alertness. Forsman et al. [1] created a method for detecting driver drowsiness when the driver experiences moderate levels of fatigue. This method allows for adequate time for the driver to reach a rest stop. Although vehicle-based methods for detecting drowsiness are non-invasive, they may not be as accurate in detecting drowsiness because they rely on the road conditions and the driver's driving skills.

The second category of methods for detecting drowsiness involves measuring the driver's condition by using electronic devices attached to the skin. This category includes techniques such as methods include electroencephalography (EEG), electrocardiography (ECG), and electrooculogram (EOG).Numerous studies have indicated that among various indicators for detecting drowsiness, methods based on EEG signals are the most practical and promising. Lin et al. [10] introduced a new brain-computer interface system that can collect and analyze EEG signals in real-time to detect and alert drivers of drowsiness. The system achieved an average sensitivity of 88.7% and a positive predictive value of 76.9%.

Gao et al.[11] devised a spatial temporal convolutional neural network, referred to as the ETCNN, that was capable of detecting driver drowsiness by analyzing EEG signals. Their method achieved a high accuracy of 97.37%. Despite their high level of accuracy, these devices are not frequently utilized because of their practical limitations.

The third approach relies on visual features, primarily analyzing the state of the driver's eyes, mouth, facial expressions, and head position [5].In the drowsy state, the frequency of eye blinking and the duration of eye closure are different from those in the normal state. Therefore, many methods for detecting drowsiness focus on detecting changes in the eyes.[4][6][7].

III. METHODOLOGY

The proposed method for determining driver sleepiness is introduced in this section. The input for the system is obtained by capturing an image of the driver through the webcam. Initially, the system will detect and extract the face from the image with created Region of Interest (ROI).

Next, the system will locate the eye region within the face. This area will then be used as input data for the CNN algorithm, which will classify different levels of drowsiness. Once the eye regions have been identified, the system will execute tasks to detect eye closures. Based on the results of these tasks, the system will evaluate the degree of drowsiness exhibited by the driver.

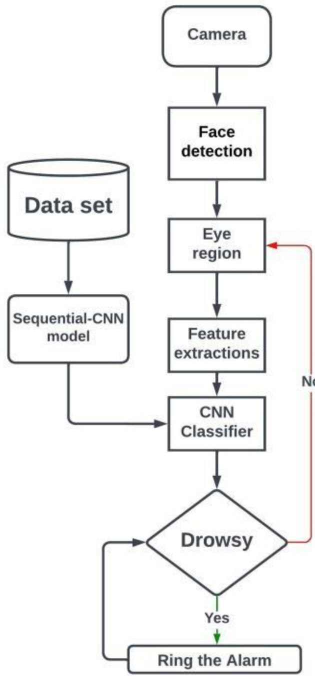

Figure 1 : Workflow of the system

A. FACE DETECTION

The face detection in real time is done by Viola Jones. The Viola Jones algorithm has four main steps.

1.Selecting Haar-like features
2.Creating an integral image
3.Running AdaBoost training
4.Creating classifier cascades

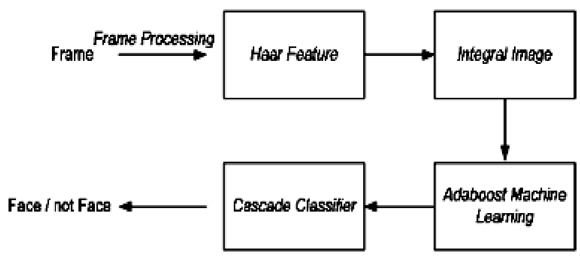

Figure 2 : Face Detection Steps Done By Viola Jones

For detection, the method employs a Haar feature basis filter. Human faces share some characteristics, and Haar Features can be used to match them.

Haar-like features refer to digital image characteristics that are employed for object recognition. Certain characteristics of the human face are universal, such as the nose region being brighter than the eye region and the eyes region being darker than its neighbouring pixels. By subtracting the total number of pixels inside clear rectangles from the total number of pixels inside shaded rectangles, the value of every given feature may be determined.

The integral image is utilized to rapidly and efficiently compute the sum of pixel values within an entire image or a rectangular region of the image.

Over 160,000 features are present in the 24x24 detector window, however only a few of these elements are significant for identifying a face. The AdaBoost method is used to find the best features among the 160,000 features. Adaboost is short for adaptive boosting.

Each Haar-like feature is a weak classifier. The final classifier is formulated as a combination of weak classifiers, expressed as a linear equation. In the AdaBoost learning algorithm, stronger classifiers are assigned larger weights.

F(x) is the strong classifier and α f(x) is the weighted combination of weak classifiers.

$$F(x) = \alpha_1 f_1(x) + \alpha_2 f_2(x) + \alpha_3 f_3(x) \ldots \qquad (1)$$

The cascade's job is to quickly eliminate non-faces in order to avoid wasting time and calculations. We set up a cascaded system in which we divide the task of identifying a face into many steps. This is designed to remove non-faces rapidly, saving time and computational resources. Because each classifier represents a feature of a human face, a positive detection effectively states, "Yes, this subregion includes all of the characteristics of a human face." Yet, if one feature is missing, it rejects the entire subregion.

B. *EYE DETECTION*

The most essential aspect that helps detect driver fatigue is the state of eyes, i.e. open or closed. The position of the driver's eyes are determined by using Viola Jones. The system takes an image of a person's face and detects their eyes. To process each eye image, first it resizes it to a fixed size, normalizes the pixel values, and then converts it to an array. The array is then expanded to match the input shape of the neural network model, which predicts whether the eye is open or closed.

If both eyes are classified as closed, the code starts a counter and checks if the counter exceeds a certain threshold to trigger an alarm, indicating that the driver may be falling asleep.

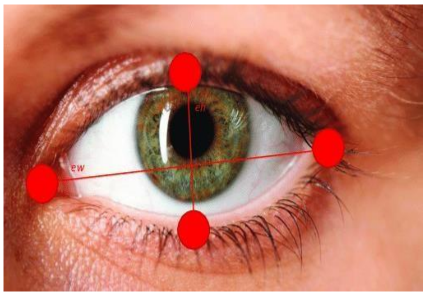

Figure 3 : Eye Detection

C. *CLASSIFICATION*

We employed the Keras-built sequential model with CNN. A convolutional neural network is a type of deep neural network that works exceptionally well for image classification and computer vision tasks. A CNN is made up of three layers: an input layer, an output layer, and a hidden layer, which can contain several layers.

The key idea behind CNN is to learn local patterns or features from images by applying a series of convolutional filters, followed by pooling layers to extract the most important features.

Convolutional layers, pooling layers, and fully connected layers are the fundamental components that constitute a CNN.

Convolutional layers perform a convolution operation on the input image using a set of learnable filters to extract local features or patterns. The output of a convolutional layer is a feature map.

Pooling layers are designed to shrink the dimensions of feature maps by employing techniques such as max pooling or average pooling, which effectively down-sample the features. This helps in reducing the computational complexity of the network and preventing overfitting.

Fully connected layers perform a classification task on the learned features by mapping the extracted features to the output classes.

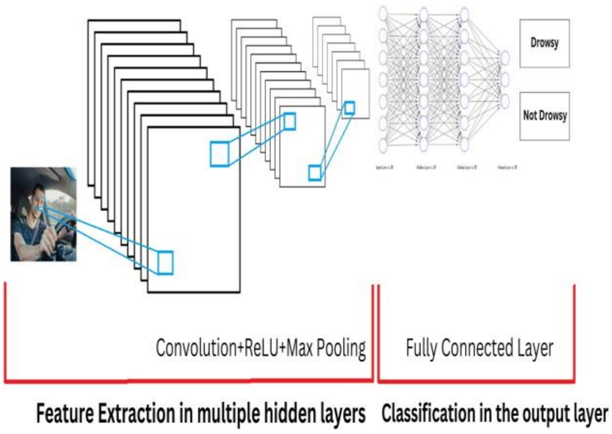

Figure 4 : CNN Architecture

The sequential model starts with a convolutional layer (Conv2D) that applies a filter to the input image and produces a feature map. This layer has 7,168 trainable parameters. The output of the convolutional layer is passed through a max pooling layer (MaxPooling2D) that reduces the size of the feature map by taking the maximum value of each pooling window.

Following the initial max pooling layer, the second convolutional layer (Conv2D) implements an additional filter on the output and generates an additional feature map. This layer consists of 295,040 parameters that can be trained. The outcome of this convolutional layer is subsequently subjected to a max pooling layer (MaxPooling2D) that further reduces the dimensions of the feature map.

Another filter is applied to the output of the second max pooling layer by the third convolutional layer (Conv2D), resulting in another feature map. This layer has 73,792 trainable parameters. The feature map is then passed through another max pooling layer (MaxPooling2D) to reduce its size.

Another filter is applied to the output of the third max pooling layer to produce another feature map in the fourth convolutional layer (Conv2D), which has 18,464 trainable parameters. The output is again passed through a max pooling layer (MaxPooling2D) to further reduce the feature map size. The flattened output of this max pooling layer is then processed through a dropout layer (Dropout) to prevent overfitting.

After the dropout layer, the resulting output is fed into two Dense layers, The first Dense layer has 100,416 parameters that can be trained, while the second Dense layer has 260 trainable parameters. The tensor produced by these layers contains four values, which indicate the predicted probabilities for each of the four classes that are present.

D. PERFORMANCE ANALYSIS

The performance of the proposed system can be analyzed using following parameters for measuring classification accuracy:

True Positive (TP): Closed eye status is detected as correct , and the eye is closed.

True Negative (TN): Opened eye status is detected as the correct one , and the eye is opened.

False Positive (FP): Opened eye status is incorrectly detected as closed eye.

False Negative (FN): Closed eye status is incorrectly detected as open eye.

The accuracy is calculated in percentage using equation (2):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100$$

References	Methods	Accuracy in %
B. N. Manu [16]	Binary SVM with Linear kernel	94.58
B. Reddy et al. [17]	MTCNN And DDDN	91.6
F. Zhang et al. [13]	CNN	95.18
J. Gwak [14]	RF	81.4
Jue Li[12]	SVM	79.5%-85.0%
Rahman[6]	SVM	92%
Zhang [15]	boost-LBP + SVM	85.9
Proposed Method	CNN	95.62%

Table 1: Comparison of the state-of-the-art methods with proposed method.

IV. EXPERIMENTAL RESULTS

The model was trained for 50 epochs. During the training process, the model achieved an accuracy of 95.62% on the training dataset. The validation dataset was also evaluated, and the model achieved an accuracy of 96.19%.

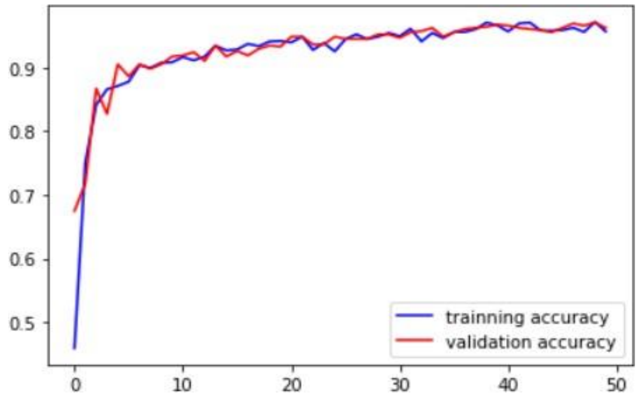

Figure 5 : Model accuracy

The drowsiness detection is shown in below figures.

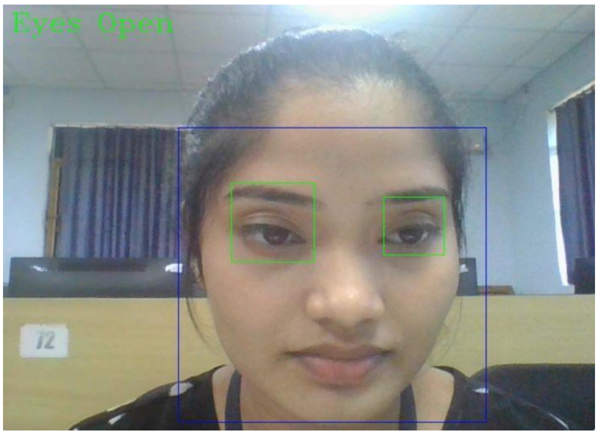

Figure 6: Normal eye detection when eyes are open

Figure 7: Pop out alert drowsiness notification onframe webcam when eyes are closed

V. CONCLUSION

This paper proposes a drowsiness detection system based on eye detection.. The role of the system is to detect face and eyes from the video frame and extract the features of eyes which will serve as an input to the CNN model which will classify the images and predict by comparing it with the threshold and detect level of drowsiness.

According to the experimental results, it successfully detects person during drowsy condition. However, there is still space for the performance improvement.

Future work could focus on collecting more diverse data that includes a wider range of individuals, lighting conditions, and driving environments to improve the accuracy and robustness of the system. Could incorporate other physiological indicators, such as heart rate variability, electroencephalography (EEG), and skin conductance, to improve the accuracy of the detection system. Could also explore the possibility of providing real-time feedback to the driver, such as adjusting the temperature or playing music to help the driver stay alert.

REFERENCES

[1] Forsman PM, Vila BJ, Short RA et al (2013) Efficient driver drowsiness detection at moderate levels of drowsiness. Accid Anal Prev 50:341–350

[2] Liu CC, Hosking SG, Lenne MG (2009) Predicting driver drowsiness using vehicle measures: recent insights and future challenges. J Saf Res 40(4):239–245

[3] A. D. McDonald, C. Schwarz, J. D. Lee, and T. L. Brown, “Real-Time Detection of Drowsiness Related Lane Departures Using steering Wheel Angle,” Proc. Hum. Factors Ergon. Soc. Annu. Meet., vol. 56, no. 1, pp. 2201–2205, 2012.

[4] Mandal B, Li L, Wang GS et al (2017) Towards detection of bus driver fatigue based on robust visual analysis of eye state. IEEE Trans Intell Transp Syst 8(3):545–557.

[5] V. U. Maheswari, R. Aluvalu, M. P. Kantipudi, K. K. Chennam, K. Kotecha and J. R. Saini, "Driver Drowsiness Prediction Based on Multiple Aspects Using Image Processing Techniques," in IEEE Access, vol. 10, pp. 54980-54990, 2022, doi: 10.1109/ACCESS.2022.3176451.

[6] Rahman, H.; Ahmed, M.U.;Barua, S.; Funk, P.; Begum, S. Vision-Based Driver’s Cognitive Load Classification Considering Eye Movement Using Machine Learning and Deep Learning. Sensors 2021, 21, 8019. https://doi.org/10.3390/ s21238019.

[7] .X. -S. Li, Z. -Z. Fan, Y. -Y. Ren, X. -L. Zheng and R. Yang, "Classification of Eye Movement and Its Application in Driving Based on a Refined Pre-Processing and Machine Learning Algorithm," in IEEE Access, vol. 9, pp. 136164-136181, 2021, doi: 10.1109/ACCESS.2021.3115961.

[8] LaRocco J, Le MD, Paeng DG (2020) A systemic review of available low-cost EEG headsets used for drowsiness detection. Front Neuroinform. https://doi.org/10.3389/fninf.2020.00001.

[9] Ma Y, Zhang S, Qi D et al (2020) Driving drowsiness detection with EEG using a modified hierarchical extreme learning machine algorithm with particle swarm optimization: a pilot study. Electronics 9(5):775.

[10] Lin CT, Chang CJ, Lin BS et al (2010) A real-time wireless brain–computer interface system for drowsiness detection. IEEE Trans Biomed Circuits Syst 4(4):214–222.

[11] Gao Z et al (2019) EEG-based spatio-temporal convolutional neural network for driver fatigue evaluation. IEEE Trans Neural Netw Learn Syst 30(9):2755–2763. https://doi.org/10.1109/TNNLS.2018.2886414.

[12] Jue Li, Heng Li, Waleed Umer, Hongwei Wang, Xuejiao Xing, Shukai Zhao, Jun Hou, Identification and classification of construction equipment operators' mental fatigue using wearable eye-tracking technology, Automation in Construction, Volume 109, 2020, 103000, ISSN 0926-5805, https://doi.org/10.1016/j.autcon.2019.103000.

[13] F. Zhang, J. Su, L. Geng, and Z. Xiao, “Driver fatigue detection based on eye state recognition,” *Proc. - 2017 Int. Conf. Mach. Vis. Inf. Technol. C. 2017*, pp. 105–110, 2017.

[14] J. Gwak, M. Shino and A. Hirao, "Early Detection of Driver Drowsiness Utilizing Machine Learning based on Physiological Signals, Behavioral Measures, and Driving Performance," 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 2018, pp. 1794-1800, doi: 10.1109/ITSC.2018.8569493.

[15] Yan Zhang and Caijian Hua, “Driver fatigue recognition based on facial expression analysis using local binary patterns,” Optik, vol. 126, pp. 4501–4505, 2015.

[16] B. N. Manu, “Facial features monitoring for real time drowsiness detection,” Proc. 2016 12th Int. Conf. Innov. Inf. Technol. IIT 2016, pp. 78–81, 2017.

[17] B. Reddy, Y. Kim, S. Yun, C. Seo, and J. Jang, “Real-time Driver Drowsiness Detection for Embedded System Using Model Compression of Deep Neural Networks,” Comput. Vis. Pattern Recognit. Work., 2017.

[18] M. D. Putro, Wahyono and K. -H. Jo, "Multiple Layered Deep Learning Based Real-time Face Detection," 2019 5th ICST, Yogyakarta, Indonesia, 2019, pp. 1-5, doi: 10.1109/ICST47872.2019.9166172.

[19] R. Subban and S. Soundararajan, "Human face recognition using facial feature detection techniques," 2015 International Conference

on Green Computing and Internet of Things (ICGCIoT), Greater Noida, India, 2015, pp. 940-947, doi: 10.1109/ICGCIoT.2015.7380598.

[20] S. Saypadith and S. Aramvith, "Real-Time Multiple Face Recognition using Deep Learning on Embedded GPU System," 2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Honolulu, HI, USA, 2018, pp. 1318-1324, doi: 10.23919/APSIPA.2018.8659751.

[21] M. Omidyeganeh, A. Javadtalab and S. Shirmohammadi, "Intelligent driver drowsiness detection through fusion of yawning and eye closure," 2011 IEEE International Conference on Virtual Environments, Human-Computer Interfaces and Measurement Systems Proceedings, Ottawa, ON, Canada, 2011, pp. 1-6, doi: 10.1109/VECIMS.2011.6053857.

[22] B. -G. Lee and W. -Y. Chung, “Driver Alertness Monitoring Using Fusion of Facial Features and Bio-Signals,” in IEEE Sensors Journal, vol. 12, no. 7, pp. 2416-2422, July 2012, doi: 10.1109/JSEN.2012.2190505.

[23] Y. Liang, M. L. Reyes and J. D. Lee, "Real-Time Detection of Driver Cognitive Distraction Using Support Vector Machines," in IEEE Transactions on Intelligent Transportation Systems, vol. 8, no. 2, pp. 340-350, June 2007, doi: 10.1109/TITS.2007.895298.

[24] A. Sinha, R. P. Aneesh and S. K. Gopal, "Drowsiness Detection System Using Deep Learning," 2021 Seventh International Conference on Bio Signals, Images, and Instrumentation (ICBSII), Chennai, India, 2021, pp. 1-6, doi: 10.1109/ICBSII51839.2021.9445132.

[25] G. Li, B. -L. Lee and W. -Y. Chung, "Smartwatch-Based Wearable EEG System for Driver Drowsiness Detection," in IEEE Sensors Journal, vol. 15, no. 12, pp. 7169-7180, Dec. 2015, doi: 10.1109/JSEN.2015.2473679.

[26] V. Valsan A, P. P. Mathai and I. Babu, "Monitoring Driver’s Drowsiness Status at Night Based on Computer Vision," 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), Greater Noida, India, 2021, pp. 989-993, doi: 10.1109/ICCCIS51004.2021.9397180.

[27] S. S. Kulkarni, A. D. Harale and A. V. Thakur, "Image processing for driver's safety and vehicle control using Raspberry Pi and webcam," 2017 IEEE International Conference on Power,