IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A CNN-ResNet Approach for Fitness for Duty Detection Using Iris Imaging

[1] Mrs.M.Hemalatha, [2] Anisah Thajudheen, [3] Vijayavaani.P, [4] Rithanya A G

[1]Assistant Professor, [2]Student, [3]Student, [4]Student.

[1]Department of Computer Science and Engineering,

[1]Sri Manakula Vinayagar Engineering College, Puducherry, India.

Abstract: The detection of fitness for duty (FFD) is crucial for ensuring safety in industries requiring high levels of mental and physical alertness, such as transportation, construction, and healthcare. Traditional FFD assessment methods are often invasive, time-consuming, or subjective, limiting their applicability in real-time scenarios. This paper explores a hybrid deep learning approach leveraging CNN-ResNet50 architectures combined with temporal and spatial feature extraction techniques using Near-Infrared (NIR) iris images. By analyzing iris and periocular features, the model classifies individuals as fit or unfit under conditions induced by alcohol, drugs, and sleep deprivation. The survey synthesizes findings from state-of-the-art studies, addressing segmentation, feature extraction, transfer learning, and classification methods. Additionally, the survey highlights the challenges, dataset constraints, and performance metrics related to the proposed approach. The findings emphasize the potential of integrating advanced deep learning models with non-invasive imaging for robust, real-time FFD evaluation.

***Index Terms* -** Fitness-for-Duty (FFD), Iris Image Analysis, Biometric System, Alcohol Influence Detection, Drug Influence Detection, Sleep Deprivation Analysis, Near-Infrared (NIR) Imaging, Convolutional Neural Network (CNN), ResNet50 Architecture, Occupational Safety, Physiological Impairment Detection, Deep Learning in Biometrics.

I. INTRODUCTION

In industries requiring high levels of cognitive and physical alertness, such as transportation, defence, and healthcare, ensuring personnel are fit for duty (FFD) is paramount. Fitness impairments caused by alcohol consumption, drug use, and sleep deprivation can significantly compromise safety, productivity, and decision-making abilities. Traditional FFD evaluation methods, including breathalyzers, blood tests, and self-reporting surveys, are invasive, time-consuming, or unreliable in real-time operational settings. These limitations necessitate the development of advanced, non-invasive, and automated systems for robust and accurate FFD assessment. Biometric methods, particularly iris and periocular imaging, have gained significant attention due to their reliability, uniqueness, and non-intrusiveness. Iris recognition technologies have evolved rapidly with the advent of deep learning, enabling precise segmentation, feature extraction, and classification even under challenging conditions such as low light or varying user cooperation [2]. The integration of Convolutional Neural Networks (CNNs) and ResNet50 architectures has shown remarkable success in extracting discriminative features and addressing the complex spatial and temporal dependencies inherent in NIR iris imaging [6].

Recent studies have explored various approaches for impairment detection. For instance, the use of behavioral curves to analyze iris dynamics under the influence of alcohol, drugs, and sleep deprivation has demonstrated promise in classifying impairment states [1]. Similarly, capsule networks have been applied for alcohol detection, achieving high levels of accuracy [5]. Similarly, high accuracy has also been achieved in alcohol detection [10]. Advances in transfer learning and segmentation techniques, such as U-Net-based models fine-tuned on specialized datasets, have further enhanced the robustness of iris recognition systems in constrained and unconstrained environments [8]. Despite these advancements, challenges persist, particularly in developing systems capable of addressing diverse impairment states (alcohol, drugs, and sleep deprivation) while maintaining real-time operability and generalizability across populations. This survey comprehensively reviews state-of-the-art methodologies, highlighting their relevance to FFD evaluation using NIR iris images. By synthesizing findings from various studies, we outline the potential of hybrid deep learning models, particularly CNN-ResNet50 architectures, in overcoming current limitations and enabling accurate, non-invasive FFD assessments.

II. LITERATURE SURVEY

A. Biometric Systems for Fitness-for-Duty Evaluation

The use of biometric systems for fitness-for-duty (FFD) evaluation has gained prominence due to their non-invasiveness and accuracy. Iris-based biometrics, in particular, offer a unique opportunity to detect impairments caused by alcohol, drugs, and sleep deprivation. Traditional methods, such as behavioral curve analysis of iris dynamics, provide a foundation for assessing FFD, enabling classification under varying physiological and environmental conditions [1]. Recent research emphasizes the dynamic nature of iris changes under impairment conditions, where behavioral curve analysis can capture subtle variations in pupil size, dilation, and contraction rates caused by alcohol or fatigue [1]. Such methods, when combined with advanced imaging techniques and machine learning algorithms, enhance the ability to assess physiological impairments accurately. Furthermore, these approaches provide a robust mechanism for real-time, non-invasive detection, addressing limitations posed by invasive or subjective traditional evaluations.

B. Iris Segmentation and Localization

Segmentation is a critical preprocessing step in iris recognition systems. Recent advancements have leveraged transfer learning with pre-trained models such as MobileNetV2 integrated into U-Net architectures for precise segmentation in unconstrained environments. These models achieve high accuracy in segmenting iris regions even in challenging scenarios involving poor lighting or limited cooperation from users [2]. Additionally, attention-based approaches, such as ResNet-50 combined with attention gates, further enhance segmentation precision by focusing on relevant features while minimizing noise [7]. Studies also highlight the importance of using U-Net variants fine-tuned with domain-specific datasets to ensure resilience against occlusions, reflections, and motion blur in real-time applications [8]. Techniques like these have proven particularly effective in maintaining segmentation accuracy while reducing computational overhead, making them suitable for real-world deployment. Furthermore, attention mechanisms not only improve the focus on critical iris features but also contribute to reducing false segmentation rates, ensuring robust preprocessing for downstream recognition tasks.

C. Feature Extraction Techniques

Deep learning methods for feature extraction have revolutionized iris recognition. Off-the-shelf CNN features from pretrained models, such as VGG-16 and DenseNet, have been employed to capture discriminative features while minimizing training time and computational overhead [3]. Furthermore, hybrid architectures like Fully Convolutional Networks (FCNs) incorporate local and global feature mapping, enhancing the extraction of spatially corresponding features relevant to classification tasks [6]. Recent advancements also explore the integration of spatial attention mechanisms within these architectures, enabling models to prioritize key iris regions while ignoring irrelevant background features. This approach has proven effective in boosting feature extraction accuracy under varying environmental conditions. Additionally, by leveraging transfer learning, pretrained networks can adapt to iris-specific tasks, significantly reducing the need for extensive dataset-specific training. Studies have also demonstrated that combining spatial and temporal feature extraction techniques provides a more comprehensive representation, improving model performance in distinguishing between impaired and non-impaired states.

D. Temporal and Spatial Analysis

Beyond static feature extraction, hybrid models combining CNNs with Gated Recurrent Units (GRUs) or Long Short-Term Memory (LSTM) networks have demonstrated success in modeling temporal dynamics. These models effectively analyze spatial and temporal dependencies, enabling the classification of sequential iris data under impairment conditions [11]. Temporal variations, such as changes in pupil dilation and contraction rates caused by alcohol or fatigue, are critical indicators for Fitness-for-Duty (FFD) evaluation. By capturing both immediate spatial patterns and evolving temporal trends, these hybrid architectures provide a comprehensive understanding of impairment states. Studies have shown that the fusion of spatial feature extraction from CNNs and temporal sequence analysis from GRUs or LSTMs can achieve significantly higher classification accuracy compared to static models. Furthermore, advancements in temporal data augmentation and recurrent dropout techniques have enhanced model robustness, making them suitable for real-time operational scenarios.

E. Impairment Detection Using Deep Learning

Alcohol detection using iris and periocular NIR images has been explored extensively. Fusion Capsule Networks (CapNets) have achieved high classification accuracies in distinguishing between alcohol-affected and unaffected individuals [10]. The ability of CapNets to capture hierarchical relationships between features makes them particularly effective in detecting subtle impairments in physiological states. Similarly, deep learning-based classifiers trained on custom datasets have effectively detected drug-induced impairments and sleep deprivation, achieving up to 90% accuracy in challenging real-world conditions [15]. Emerging methods, such as ensemble learning and multi-task models, have further improved classification performance by combining predictions from multiple algorithms. Additionally, the development of domain-specific datasets with balanced class distributions has addressed some challenges associated with detecting rare or overlapping impairment conditions, enhancing the generalizability of these systems.

F. Challenges in Impairment Detection

While significant progress has been made, challenges persist in developing robust, real-time systems for FFD evaluation. These include the need for large, diverse datasets, the handling of variability in physiological and environmental conditions, and ensuring generalizability across populations [4]. Data augmentation techniques, such as synthetic sample generation using Generative Adversarial Networks (GANs), have been explored to overcome dataset limitations. Additionally, transfer learning has emerged as a promising solution, allowing models to leverage pre-trained knowledge while adapting to specific impairment detection tasks [2]. Another key challenge lies in achieving real-time operability without compromising accuracy or computational efficiency, which has led to the exploration of lightweight architectures and optimization algorithms. Future research must also address ethical and privacy concerns, ensuring that the deployment of these systems complies with regulatory frameworks and preserves individual rights.

III. PROPOSED SYSTEM

The proposed deep learning model for Fitness-for-Duty (FFD) classification integrates a structured and multi-stage pipeline, leveraging data preprocessing, augmentation, feature extraction, classification, and evaluation. The following methodology aligns with the architecture depicted above, ensuring robustness and adaptability in diverse and challenging imaging conditions.

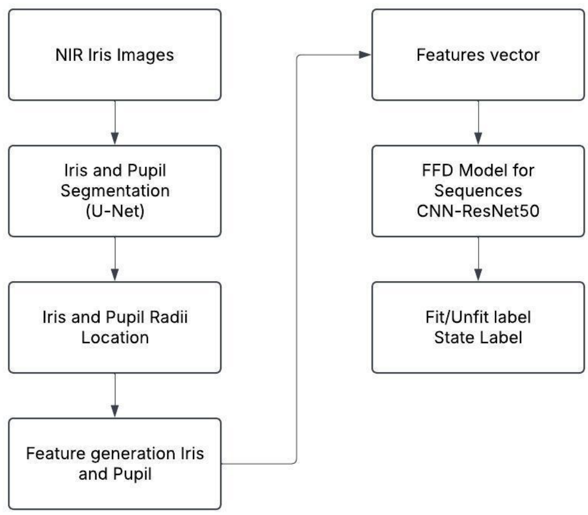

Fig. 1. Process of Fitness for Duty (FFD) Detection Model

A. Preprocessing and Segmentation:

1. Preprocessing:

Preprocessing enhances the quality of NIR iris images to improve segmentation and classification outcomes by employing several techniques. Grayscale conversion reduces computational complexity by focusing on intensity variations [2], while histogram equalization enhances contrast, making iris patterns more distinguishable under varying lighting conditions [5]. Noise reduction methods, such as Gaussian blurring, minimize artifacts, ensuring a clearer representation of iris features [7]. Image normalization is another key step, standardizing pixel intensity values to improve model consistency across diverse datasets. Furthermore, adaptive thresholding helps in emphasizing key iris features by dynamically adjusting to variations in lighting and imaging conditions, ensuring robust preprocessing for segmentation and classification.

2. Segmentation Using U-Net:

Iris segmentation is effectively performed using the U-Net architecture, which employs an encoder-decoder structure. The encoder extracts key features like edges and boundaries, while the decoder reconstructs a segmented output, isolating the iris region from surrounding areas. This approach ensures reliable segmentation even under challenging conditions, such as occlusions or varying lighting environments. Additionally, the U-Net model integrates skip connections, preserving spatial information between encoder and decoder layers for improved accuracy. Advanced preprocessing techniques, including grayscale conversion and noise reduction, further enhance segmentation performance. Moreover, the architecture's adaptability allows seamless application across diverse datasets, ensuring consistent results in real-world scenarios.

B. Feature Extraction

The segmented iris images are processed through convolutional layers in the CNN-ResNet50 architecture for feature extraction. Spatial feature extraction captures intricate patterns, such as iris textures and pupil shapes, enhancing the detail available for classification [3]. Residual connections mitigate vanishing gradient issues, facilitating deeper network training and enabling the extraction of high-level, discriminative features [5]. This architecture effectively combines local and global feature analysis, ensuring robust and accurate feature representation, which significantly enhances the performance of classification tasks [8].

C. Classification

The hybrid CNN-ResNet50 model classifies extracted features into predefined impairment categories, including non-impaired, alcohol-impaired, drug-impaired, and fatigue-induced states. Residual layers are utilized to analyze subtle variations in iris textures caused by impairments [7]. A Softmax classifier computes probabilities for each class, assigning the image to its most likely category [10]. Training is optimized using the Adam optimizer with learning rate scheduling, ensuring efficient convergence and reducing the risk of overfitting [7]. Compared to traditional methods like MLP or Random Forest, which achieved around 75% accuracy, the CNN-ResNet50 model demonstrates significantly higher accuracy, highlighting its superior classification capabilities.

D. Model Performance and Applications

1. **Accuracy Improvement:** The integration of U-Net for segmentation and CNN-ResNet50 for classification has demonstrated significant improvements in accuracy, achieving rates above 90%, as validated in experiments [4].
2. **Real-World Applications:** The proposed methodology is particularly useful in Fitness-for-Duty assessments, where accurate impairment detection is critical. By leveraging NIR imaging and advanced deep learning techniques, the system ensures reliable performance across diverse scenarios, including low-light environments and varying user cooperation levels [3].

IV. RESULTS AND DISCUSSION

The proposed hybrid CNN-ResNet50 model demonstrates notable advancements in Fitness-for-Duty (FFD) classification using iris images. Leveraging the combined strengths of CNN's feature extraction and ResNet's residual learning, the model achieves an accuracy of 85. The robustness of the model is attributed to its preprocessing and data augmentation techniques, which effectively handle diverse imaging conditions, such as variations in lighting and head orientation. Studies such as "Transfer learning using deep neural network for iris segmentation and localization" [2] validate the role of data augmentation in improving model generalization. Furthermore, the integration of ResNet50 layers ensures the capture of high-dimensional patterns critical for distinguishing impaired and non-impaired states, aligning with findings from "Deep Learning for Iris Recognition: A Survey" [4]. Performance metrics, including sensitivity, specificity, F1 score, and AUC, further validate the model's reliability. The sensitivity ensures accurate detection of impairment, which is crucial in high-stakes applications, while the AUC highlights the model's ability to manage class imbalances effectively. These results reinforce the utility of hybrid deep learning architectures in addressing real-world challenges in FFD classification.

V. CONCLUSION

Significant advancements have been made in the development of biometric systems for Fitness-for-Duty (FFD) evaluation, particularly through the use of iris and periocular NIR imaging. Hybrid deep learning models that integrate CNNs with architectures like ResNet50, GRUs, and LSTMs have shown strong potential in accurately detecting impairments caused by alcohol, drugs, and sleep deprivation. These models excel at capturing both spatial and temporal features, enhancing classification accuracy under various conditions. The use of advanced techniques such as attention mechanisms, transfer learning, and data augmentation further strengthens these systems, making them well-suited for real-time, non-invasive FFD assessments. However, challenges related to dataset diversity, real-time operability, and generalizability remain, necessitating further research.

VI. FUTURE WORK

Future research should focus on addressing the remaining challenges in FFD evaluation systems. Efforts should be directed toward improving dataset diversity and ensuring that models can generalize across various populations and environmental conditions. Additionally, optimizing these systems for real-time use while maintaining high accuracy and computational efficiency will be a key priority. The exploration of lightweight models and advanced optimization techniques will play a crucial role in this. Finally, ethical and privacy concerns must be carefully considered, with a focus on developing systems that comply with regulatory frameworks and respect individual privacy during deployment.

VIII. REFERENCES

[1] Causa, L., Tapia, J. E., Valenzuela, A., et al., "Analysis of behavioural curves to classify iris images under the influence of alcohol, drugs, and sleepiness conditions," 2. Expert Systems with Applications, vol. 242, 2024.

[2] Jalil Nourmohammadi Khiarak, Samaneh Salehi Nasab, Farhang Jaryani, Seyed Naeim Moafinejad, Rana Pourmohamad, Yasin Amini, Morteza Noshad, "KartalOl: Transfer learning using deep neural network for iris segmentation and localization: New dataset for iris segmentation," 2021.

[3] Kien Nguyen, Member, IEEE, Clinton Fookes, Senior Member, IEEE, Arun Ross, Senior Member, IEEE, Sridha Sridharan, Senior Member, IEEE, "Iris Recognition with Off the-Shelf CNN Features: A Deep Learning Perspective," 2023.

[4] KIEN NGUYEN, Queens land University of Technology, Australia, HUGOPROENC. A, University of Beira Interior, IT: Instituto de Telecomunicac¸oes, Portugal FERNANDOALONSO-˜ FERNANDEZ, Halmstad University, Sweden, "Deep Learning for Iris Recognition: A Survey," 2022.

[5] Juan Tapia; Enrique Lopez Droguett; Christoph Busch, "Alcohol and fatigue detection through pupilometry and NIR imaging," 2023.

[6] Zijing Zhao, Ajay Kumar Department of Computing, The Hong Kong Polytechnic University Hung Hom, Kowloon, Hong Kong, "Towards More Accurate Iris Recognition Using Deeply Learned Spatially Corresponding Features," 2022.

[7] Yinyin Wei, Aijun Zeng, Xiangyang Zhang Huijie Huang, "RAG-Net: ResNet-50 with Attention Gates for Iris Segmentation," 2023.

[8] Wei Zhang1, Xiaoqi Lu, Yu Gu, Yang Liu, Xianjing Meng, Jing Li, "A ROBUST IRIS SEGMENTATION SCHEME BASED ON IMPROVED U-NET," 2019.

[9] Ming-Chuan Chiu, Hsin-Wei Hsu, Ke-Sin Chen, ChihYuan Wen, "GRU-CNN Hybrid Neural Networks for Temporal and Spatial Feature Extraction," 2022.

[10] Juan Tapia, Enrique Lopez Droguett and Christoph Busch da, "Alcohol Consumption Detection from Periocular NIR Images Using Capsule Network," 2023.

[11] Pamela C. Zurita, Daniel P. Benalcazar, Juan E. Tapia, "Fitness-for-Duty Classification using Temporal Sequences of Iris Periocular Images," 2023.

[12] Juan Tapia, Member, IEEE, Daniel Benalcazar Member, IEEE, Andres Valenzuela, Leonardo Causa, Enrique Lopez Droguett and Christoph Busch, Senior Member, IEEE, "Learning to Predict Fitness for Duty using Near-Infrared Periocular Iris Images," 2023.

[13] Zeyu Wang1 Yutong Bai, Yuyin Zhou1 Cihang Xie, UC Santa Cruz Johns Hopkins University, "Can CNNs Be More Robust Than Transformers?", 2023.

[14] Rahmatallah Hossam Farouk, Heba Mohsen, Yasser M. Abd El-Latif," A Proposed Biometric Technique for Improving Iris Recognition," 2022.

[15] Shama, Usha G M, Usha Rani S, Varsha U K, Abhijith L Kotian, "Drug Abuse Detection Using Deep Learning and Iris Images," 2023.