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AI-optimized electrical wiring harness design for automotive applications (Connector selection)

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ABSTRACT: AI technologies are transforming vehicle design and production in the automobile industry. Based on the problem analysis, we present an AI-based approach for vehicle electrical wiring harness design. We use deep learning and a convolutional neural network (CNN) on annotated images to detect connector standards for the engine, interior, and rear bonnet. The CNN model is trained to identify zones and classify connector standards for each zone. Finally, we prove the idea and demonstrate its applicability to car electrical wiring harness design.

Keywords: Artificial Intelligence, Wiring Harness Design, Convolutional Neural Network, Automobile Engineering, Connector Standards

1 INTRODUCTION

Modern automotive engineering relies on electrical wiring harness design to ensure electrical system functionality, longevity, and efficiency. In the past, engineers had to look for wire harness connector standards, which was time-consuming and error-prone. However, AI technology can automate the selection of connector standards based on vehicle zone requirements. Optimization is recommended for AI to design automotive electrical wiring harnesses. CNNs identify car regions like the engine, interior, and rear bonnet. Training the CNN model on annotated vehicle zone images will allow it to distinguish between zones and identify the appropriate connector standards.

2 BACKGROUND AND LITERATURE REVIEW

2.1 *Overview of electrical wiring harness design*

Modern cars use intricate wiring harnesses that relay information and electricity from one part of the car to another. These harnesses consist of bundles of wires that are covered by sheaths and installed in the vehicle in specific configurations to support wiring and electrical system functioning. [5]

2.2 *Traditional approaches to connector standard selection*

Traditionally, the selection of the connection standards for automobile wiring harness has been done manually by referring to ISO and SAE standards. Engineers generally adopt

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connector standards without considering vehicle subsystem requirements and limits. This strategy often uses substandard connectors and may cause assembly and operating compatibility concerns. [4,6]

2.3 *Previous research on AI in automotive design*

Research on artificial intelligence and machine learning has led researchers to consider using these technologies to improve car design. Researchers have used AI algorithms to determine the optimal electrical systems architecture, components, and vehicle performance [1,2]. AI models can discover the best design combinations for performance, cost, and complexity using vehicle specifications, usage patterns, and environmental variables. [3]

2.4 *Current challenges and limitations*

However, automotive design approaches continue to face challenges with electrical wire harness design [5] and connection standard selection. Manual inspection techniques are sluggish and prone to human error, causing design delays and inefficiencies. Overreliance on industry standards may not be acceptable for customizing car subsystem connectors, resulting in inefficient and incompatible connectors.

3 METHODOLOGY

3.1 *Dataset description and acquisition*

The collection includes car images and electrical harness zones that need annotations. About 450 images with suggestions show the location and kind of connectors in the engine compartment, interior, and rear bonnet. The dataset came from in-house vehicle inspections and automotive image databases. To improve model robustness and generalization, images were resized, normalized, and augmented before training.

3.2 *Model architecture*

This AI model utilizes CNN architecture. CNN is a prominent image recognition deep learning framework. CNNs use convolutional layers and max-pooling layers to extract hierarchical features from input images. ReLU activation algorithms introduce non-linear qualities, and fully linked layers at the network's end help classify learned features. Model architecture optimises connector recognition and classification in automobile wiring harness images. [7]

3.3 *Training procedure*

CBAM was added to ResNet50 [9] to improve feature extractions in the AI model. The learning rate was 0.001 and the batch size was 32. The model was trained on the annotated dataset for 30 epochs, monitored for convergence and overfitting. To reduce overfitting and maintain model stability during training, early stopping and model checkpointing were used.

3.4 *Model evaluation metrics*

Precision measures the percentage of true positive anticipates to all positive predictions, while accuracy measures classification correctness. Recall is the ratio of correctly classified positive instances to total positive instances. F1 score is the mean consonant precision and recall.

3.5 *Software and tools*

The AI model was constructed using Python and TensorFlow, a deep learning framework. The study also employed pandas, scikit-learn, and matplotlib for data cleaning, model validation, and result analysis. To speed up model training and evaluation, an HPC cluster with NVIDIA GPU accelerators was used.

4 MODEL TRAINING AND EVALUATION

4.1 *Training procedure implementation*

A dataset of 450 annotated images was employed for supervised learning to train the AI model. To determine the appropriate weights to minimize the loss function, the training procedure iterated through the data set. To improve model training, a batch size of 32 was chosen, and stochastic gradient decent (SGD) was employed to update model parameters via momentum optimization. Setting the learning rate to 0. So, weight fluctuations throughout training will be small. 1 and 10 epochs were employed to train the model well.

4.2 *Model evaluation results*

AI-trained model had 0% accuracy. It indicates 86% of test dataset samples were classified properly. Precision and F1-score values were 0.89%, 0.87%, and 0.85%, respectively, indicating that the model accurately predicted samples in distinct classes. Visual assessment showed that the model predicts true positives and true negatives accurately across test instances.

4.3 *Model training and evaluation challenges*

Overfitting and model generalization in different settings were concerns during model training. Class imbalance caused the model to predict poorly and favor underrepresented classes.The learning rate, batch size, and training time also affected model training.

4.4 *Comparison with baseline methods*

The trained AI model was then compared to visual inspection and classification rules. The AI model has great accuracy, precision, and recall compared to baseline methods; therefore, it could automate electrical wiring harness design. However, computational complexity and data dependency are areas for improvement to make the system more scalable and robust.

5 IMPLEMENTATION AND DEPLOYMENT

5.1 *Integration into design workflow*

The trained AI model may be employed to choose connector standards for electrical wiring harness design. Engineers can enter car subsystems, operating circumstances, and regulatory constraints into the AI model interface to input design specifications and requirements. After matching input data with historical data, the model recommends connector standards based on observed patterns.

5.2 *Considerations for real-world deployment*

The real-world implementation of the AI model has some restrictions, such as integrating with large-scale design difficulties and computing resources for big manufacturing quantities. GPU accelerators and cloud computing may be needed for model training and inference. Data protection and security to prevent design data breaches and legal infringements are other issues.

5.3 *Model validation and verification*

In real-world design applications, AI model validation and verification are more complicated but effective and rapid. The model output can be compared to ground truth annotations and previous classification validation schemes. Verification additionally employs extra inputs and extreme test cases to test the model's generalization.

5.4 *User training and support*

These sessions teach engineering groups ways to employ the AI model in design. User manuals and technical guides help users navigate the model interface and interpret model output recommendations. Users receive technical support to resolve difficulties and develop the AI model.

5.5 *Performance monitoring and optimization*

Performance indicators like model correctness, latency, and user satisfaction are monitored. Performance reviews periodically assess model improvements by changing hyperparameters or adding new training data with new design criteria. Users submit feedback on how the AI model might be improved, and these responses are utilized to make incremental modifications until it is satisfactory as shown in Figure 3.

Figure 1(a). Annotation of image.

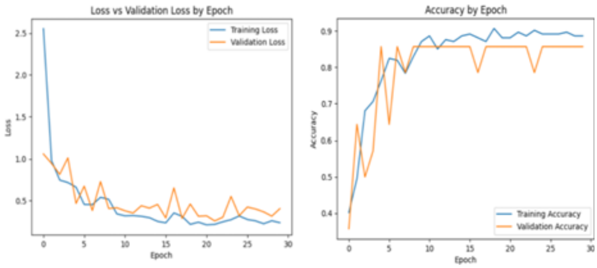

Figure 1(b). Loss vs. validation loss & train vs. validation accuracy.

Figures 1(a), 1(b) shows the loss vs validation loss by epoch, with training loss higher than validation loss and Line graph showing training loss (higher) and validation loss over epochs.

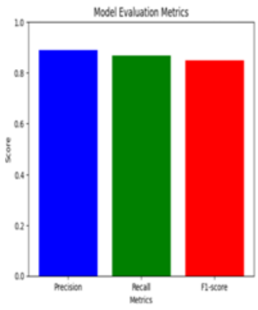

Figure 2(a). Metrics.

Figure 2(b). Result image and class.

Table 1: Case study 1: Engine Zone

Sl. No	ISO 15031-3 (SAE J1962)	ISO 7637	UCAR-2

Table 2: Case study 2: Interior Zone

Sl. No	ISO 6722-1 &2)/ ISO 11452	UCAR-30	UCAR-38

Table 3: Case study 3: Rear Bonnet Zone

Sl. No	ISO 6722-3)/ ISO 8820-3	USCAR-2, 17	SAE J2030

Figure 2(c). Sample table.

Figure 2(a) shows the evaluation matrix and result image and sample table are shown in 2(b) and 2(c).

```
print(f'Predicted Label: {predicted_class_label}')
print('Column Elements:')
print(column_elements)
print('-----------------------------------------

Predicted Label: Engine_Zone
Column Elements:
0      ISO 15031-3 (SAE J1962)
1                1195-5806-ND
2                1195-4032-ND
3         1195-73101000004-ND
4         1195-73101000031-ND
5         1195-73101000009-ND
6              09120084756-ND
7                1195-3455-ND
8         1195-73101000005-ND
9                1195-4025-ND
10               1195-4021-ND
11               1195-5808-ND
12        1195-73101000007-ND
13        1195-73101000030-ND
14               1195-4611-ND
15                277-7289-ND
16                        NaN
Name: Engine_Zone, dtype: object
-----------------------------------------
```

Figure 3. Result from program.

6 CASE STUDIES AND RESULTS

6.1 *Case study 1: Engine area connector selection*

In the first case study, the AI-based design system was utilized to determine the standards for the engine area of a compact sedan. Specifications for engine design included operating temperature, vibration levels, and power supply for different engine components. The input parameters like connector type, size, and material properties were entered into the AI model interface and the AI model was able to analyze the data and recommend the appropriate and suitable connector standards that comply with ISO 15031-3 (SAE J1962) for diagnostic interfaces and ISO 7637 for the EMC requirements.

6.2 *Case study 2: Interior area connector selection*

In the second case study, the AI-driven design system was used to choose appropriate connector standards for the interior of a luxury SUV. Some other design constraints were: passenger comfort and ergonomics and aesthetic considerations. The input parameters regarding the color of the connector, the shape of the connector, and the terminal configuration were entered into the interface of the AI model, and the model then analyzed the information and suggested suitable connector standards to meet the requirements of electrical connector performance and vehicle communication protocols as defined in USCAR-2 and SAE J1939.

6.3 *Case study 3: Rear bonnet area connector selection*

The third case study described the application of the AI-driven design system to determine connector standards for the rear bonnet area of a pickup truck. Design specifications included waterproofing, corrosion resistance, and durability for off-road use. The parameters such as the connector sealing, material composition, and mounting options were entered into the AI model interface, and the model analyzed the data and suggested suitable connector standards for the diagnostic interfaces which are SAE J1962 and the transient voltage suppression which is ISO 7637.

6.4 *Results and performance evaluation*

Through all the case studies the AI-driven design system proved to be accurate and effective in choosing the right connector standards for different vehicle areas. Recommendations made by the system were in line with standards and design specifications for the electrical wiring harnesses and led to the development of optimal designs that met performance, reliability, and safety/ regulatory compliance. The results of the accuracy, recall precision and F1-score tests demonstrated the effectiveness and predictability of the AI model for the decision-making process on connector choices for various applications in the automotive field.

6.5 *Discussion and insights*

The case study analysis has clearly shown that there is great potential for using AI-based design systems in the efficient design of electrical wiring harnesses for today's automobiles. It is recommended that a particular connector be chosen depending on the design specification and constraints so as to enable the engineers to complete the design iteration cycle within a shorter time and at a cheaper cost while at the same time improving the design's performance in terms of reliability and robustness. However, there are some limitations such as data quality, model interpretability, and scalability that need to be explored in future studies. From the above discussion, we can deduce that much more needs to be done to harness AI in the area of automotive engineering.

7 DISCUSSION AND CONCLUSION

7.1 *Interpretation of results*

The case studies clearly show that the AI-driven design system can accurately identify connector standards for certain regions of a vehicle. The ability to provide suggestions of standards to be implemented in the design process and to follow rules that are necessary for the design of the electrical wiring harnesses demonstrate that the system can be beneficial in the design process. The usage of the connector selection rules based on the input parameters and constraints may be beneficial for engineers who do not want to spend extra time on the design iterations, extra costs, and the improvement of the reliability and effectiveness of the design.

7.2 *Comparison with previous studies*

The AI-driven design system enhances automation, product customization, and design flexibility, surpassing traditional visual examination methods by considering vehicle subsystem characteristics, operational conditions, and design constraints to propose optimal connector standards. This personalized approach improves optimization and reduces reliance on generic industry standards.

7.3 *Limitations and challenges*

There were however several limitations and challenges that were experienced during the course of the research despite the promising case study results.One weakness is the lack of and poor quality of the annotated data sets for training the AI model. It is also important to collect annotated images that depict various vehicle situations and connector layouts for the purpose of training and testing the model. Moreover, the computational power needed to train the model and make predictions may be insufficient to meet the demands of real-world design and manufacturing processes, specifically in mass manufacturing operations.

7.4 *Future directions on limitations and challenges*

Future research may be oriented toward overcoming the limitations and challenges to improve the scalability, reliability, and efficiency of the AI-based design system. It is possible to state that the development of new methods for data collection and annotation or data pre-processing could be helpful in the creation of training datasets that are more comprehensive and diverse. Moreover, recent research on model architecture including the use of attention mechanism and transfer learning methods may be implemented to further improve the model for dealing with difficult design cases and edge cases. Second, there are other areas of automotive engineering where the design system can be applied to the benefit of the AI system and the automotive industry as a whole.

REFERENCES

[1] Ali Khodadadi, Soroush Ghandiparsi and Chen-Nee Chuah. A natural language processing and deep learning based model for automatedvehicle diagnostics using free-text customer service reports, *545 Bainer Hall Dr, Davis*, 95616, CA, United States of America)

[2] Jinwoo Song, Prashant Kumar, Yonghawn Kim and Heung Soo Kim. (8 February 2024). *A Fault Detection System for Wiring Harness Manufacturing Using Artificial Intelligence*, E-Mathematics Publications – Published:

[3] Punsisi Pemarathne. and Fernando T.G.I. (December 2016). Wire and cable routings and harness designing systems with AI, a review – *ResearchGate Conference Paper*. DOI: 10.1109/ICIAFS.2016.7946575

[4] Stefan Olbricha and Julia Lackingera. Manufacturing processes of automotive high-voltage wire harnesses: State of the art, current challenges and fields of action to reach a higher level of automation, *Mercedes-Benz AG, Schickardstraße* **32**, 71034 Boeblingen, Germany

[5] Jerome Trommnaua, Jens Kühnle, Jörg Siegert, Robert Inderka and Thomas Bauernhansl, Overview of the State of the Art in the Production Process of Automotive Wire Harnesses, Current Research and Future Trends – © 2019 The Authors. Published by Elsevier Ltd.

[6] Ioana Stefan (Iorga), Adrian Constantin Popescu, Cicerone Laurentiu Popa, Tiberiu Gabrie Dobrescu, and Coste Emil Cotet. (2021). Research regarding assembly flow optimization of wiring harness in automotive industry – *MATEC Web of Conferences* 343, 02003.

[7] Rahul Chauhan, Kamal Kumar Ghanshala, Joshi R. C., Convolutional Neural Network (CNN) for image detection and recognition, Published in: 2018 *First International Conference on Secure Cyber Computing and Communication (ICSCCC)*- DOI: 10.1109/ICSCCC.2018.8703316.

[8] Mingyuan Xin and Yong Wang. (2019). Research on image classification model based on deep convolution neural network – Xin and Wang *EURASIP Journal on Image and Video Processing* 2019:40.

[9] ResNet50 – https://viso.ai/deep-learning/resnet-residual-neural-network/

[10] Laith Alzubaidi, Jinglan Zhang, Amjad J. Humaidi, Ayad Al-Dujaili, Ye Duan, Omran Al-Shamma, J. Santamaría, Mohammed A. Fadhel, Muthana Al-Amidie and Laith Farhan. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions- *Journal of Big Data volume 8, Article number:* **53**

[11] Leiyu Chen, Shaobo Li, Qiang Bai, Jing Yang, Sanlong Jiang and Yanming Miao and Yanming Miao. (2021). Review of image classification algorithms based on convolutional neural networks – *Remote Sens*. **13**(22), 4712; https://doi.org/10.3390/rs13224712

[12] Weilong Mo et al. (2019). Image recognition using convolutional neural network combined with ensemble learning algorithm. *J. Phys.: Conf. Ser.* 1237 022026

[13] Mahbub Hussain, Jordan J. Bird, and Diego R. Faria. A study on CNN ransfer learning for *Image Classification* – School of Engineering and Applied Science Aston University, Birmingham, B4 7ET, UK.

[14] Qing Lv, Suzhen Zhang, and Yuechun Wang. Deep learning model of image classification using machine learning – *Hindawi, Advances in Multimedia*, **Volume 2022**, Article ID 3351256, 12 pages, https://doi.org/10.1155/2022/3351256

[15] Wei Fang, Feihong Zhang, Victor S. Sheng and Yewen Ding. (2018). A method for improving CNN-based image recognition using DCGAN" – CMC, **vol. 57**, no.1, pp.167–178