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Course Design and Implementation of Fault Diagnosis for New Energy Vehicle Power Batteries based on Deep Learning

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Abstract

This paper focuses on the design and implementation of the course on fault diagnosis of power batteries for new energy vehicles, exploring the process of integrating deep learning technology with power battery fault diagnosis and transforming it into teaching content. It plans the teaching module of the diagnostic model, introduces the teaching methods and case implementation paths, and analyzes the teaching effect evaluation and the direction of course optimization. It clarifies the course positioning goals, enabling students to master the principles, fault modes, and model applications, and cultivate problem-solving abilities; it builds a content system centered on data, algorithms, etc., integrating knowledge from multiple disciplines; it designs a theory-practice balanced plan, plans progressive cases and projects, and builds a skill chain; it proposes diversified teaching assessment and resource construction ideas, establishes an assessment system, and discusses the construction of a hybrid experimental platform. The innovative features of the course lie in focusing on technology integration, emphasizing engineering practice, solving industrial problems, filling teaching gaps, providing a knowledge system, and delivering compound talents to support industrial development.

Keywords

Deep Learning; New Energy Vehicles; Power Batteries; Fault Diagnosis; Course Design.

1. Introduction

With the global energy transition and the advancement of the "dual carbon" goals, the new energy vehicle industry has experienced explosive growth. As the "heart" of these vehicles, the performance, safety, and reliability of power batteries determine the overall operational quality and user safety of the vehicles. However, under complex operating conditions, the internal electrochemical processes of power batteries are intricate, and they are prone to various faults, which are the main cause of safety incidents. Traditional fault diagnosis methods rely on expert experience and other factors, and they face limitations such as difficulty in feature extraction when dealing with real vehicle operation data. Deep learning techniques, such as CNN, RNN, and their variants, with their capabilities of automatic feature extraction and complex pattern recognition, provide tools for processing power battery time series data and mining fault features. Research shows that data-driven deep learning methods have significant advantages in battery fault diagnosis and other areas. Therefore, integrating deep learning with power battery fault diagnosis is a technological development trend and an industrial demand[1]. Against this backdrop, combining deep learning with power battery fault diagnosis and incorporating it into the curriculum is of great significance. From the perspective of talent cultivation, it can respond to the national demand for "AI + automotive" composite talents and help students master the full chain of skills. From the perspective of industrial development, it can help popularize the concept of intelligent operation and maintenance, transform academic achievements into practical capabilities, and provide support for the development of the industry.

2. Current Research Landscape

In the field of power battery fault diagnosis technology, both domestic and international research has rapidly evolved from model and knowledge-based approaches to data-driven methods. Foreign research started earlier and has a solid foundation in battery mechanism modeling and state estimation algorithms. In recent years, the focus has shifted to using machine learning and deep learning to process battery big data, such as employing LSTM-RNN networks and integrating attention mechanisms[2], providing a model basis for intelligent diagnosis and promoting engineering applications. Domestic scholars have conducted extensive data-driven research, such as combining data preprocessing with CNN for fault diagnosis and using real vehicle data and BP-AdaBoost algorithms to estimate battery health status. Prediction and early warning research covers multiple dimensions, and models have expanded to hybrid architectures to enhance accuracy and interpretability[3]. However, current research mainly focuses on algorithm model improvement and validation, and the systematic integration of key technologies and the formation of a complete knowledge system for engineering education and practice remain blank spots. In terms of course construction, universities at home and abroad generally offer courses such as "New Energy Vehicle Technology", and some institutions explore interdisciplinary integration. However, courses that systematically integrate deep learning theory with power battery fault diagnosis for new energy vehicles are scarce. Existing courses tend to focus on theory or are fragmented and lack coherent practical training. Therefore, designing bridging courses to fill the educational gap has significant innovative value[4].

3. Related Technologies

3.1 Overview of Power Battery Systems for New Energy Vehicles

The power battery system of new energy vehicles is the core power and energy storage unit of the entire vehicle. Its performance and safety determine the vehicle's range, power, and reliability. This system is an integrated product of electromechanical and thermal systems, consisting of cells, modules, battery packs, battery management systems (BMS), and thermal management systems. Cells are the basic energy storage units, working based on the reversible intercalation and deintercalation of lithium ions. Multiple cells are connected in series and parallel to form modules, which are then integrated with BMS and other components to form battery packs. The performance of the power battery system is characterized by key parameters. State of Charge (SOC) and State of Health (SOH) are the core of BMS energy management and life prediction. SOC reflects the remaining battery capacity and is the basis for estimating the vehicle's range. SOH characterizes the battery's aging and life status. Accurate estimation of SOC and SOH is crucial for ensuring battery safety, optimizing energy usage[5], and assessing residual value. Batteries are prone to failure under complex operating conditions, with main faults including internal/external short circuits, overcharging, overdischarging, lithium plating, capacity drop, and thermal runaway. Thermal runaway is the ultimate failure, with a complex evolution process involving stages such as "fault - smoke - gas leakage - fire - explosion". Internal short circuits can be triggered by membrane damage, and overcharging can damage the positive electrode structure, both potentially initiating chain exothermic reactions leading to thermal runaway. Understanding the failure mechanisms and patterns is the theoretical foundation for developing effective fault diagnosis algorithms.

3.2 Key Technologies for Battery Fault Diagnosis

To ensure the safe operation of power battery systems, it is crucial to develop efficient fault diagnosis technologies. Existing methods can be classified into three categories: model-based, signal processing-based, and data-driven. Model-based methods rely on battery mathematical models (such as ECM or electrochemical models). ECM simulates the dynamic characteristics of batteries using

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electrical components and detects anomalies by comparing online-identified parameters with health benchmarks. This method has clear physical significance, but its model accuracy is greatly affected by operating conditions and aging, and complex models have high computational costs, making them difficult to apply online. Signal processing-based methods directly extract fault features from sensor signals using tools such as wavelet transforms to capture abnormal components. They do not require precise models but are sensitive to noise, and feature extraction depends on expert experience. Traditional data-driven methods use machine learning algorithms to learn pattern classification boundaries from historical data, capable of handling nonlinear relationships[6], but their performance depends on the quality of manual feature engineering and the scale of labeled data. Current diagnosis technologies face challenges. Model-based methods have a contradiction between accuracy and real-time performance, signal processing methods have insufficient generalization ability, and traditional machine learning methods rely on a large amount of prior knowledge and have difficulty handling the deep correlations of high-dimensional time series data. Additionally, the characteristics of battery faults make early, precise, and rapid online diagnosis difficult.

3.3 Theoretical Foundation of Deep Learning

Deep learning is an important branch of machine learning, which automatically learns feature representations from raw data by constructing neural network models and has achieved breakthroughs in multiple fields, providing a new approach for battery fault diagnosis. Its core advantage lies in its powerful ability to automatically extract and represent features. Typical models suitable for battery fault diagnosis include: Stacked Autoencoder (SAE), an unsupervised learning network, used for data dimensionality reduction and anomaly detection; Convolutional Neural Network (CNN), which is good at capturing spatial local correlations and translation invariance features, and has an advantage in processing battery time series and spatial distribution information; Recurrent Neural Network (RNN) and its variants, which can handle sequence data and model long-term dependencies in time series, and are important for analyzing the dynamic process of battery parameters; Deep Belief Network, composed of stacked Restricted Boltzmann Machines, which combines unsupervised pre-training and supervised fine-tuning to improve performance. The training of deep learning models relies on loss functions, and parameters are updated through optimization algorithms to minimize the loss. Techniques such as dropout and L1/L2 regularization are used to prevent overfitting. The combination of digital twins, cloud big data platforms, and deep learning provides a cutting-edge direction for intelligent battery health management. Applying deep learning to battery fault diagnosis is expected to achieve end-to-end intelligent diagnosis and enhance the ability to identify complex and weak faults at an early stage.

4. Fault Diagnosis Course Demand Analysis and Design Objectives

4.1 Learner Demand Analysis

This course is targeted at undergraduate and graduate students majoring in vehicle engineering, electrical engineering, automation, and enterprise engineers engaged in the research and development, testing, and after-sales maintenance of new energy vehicles. Research shows that learners' prior knowledge levels and core demands are diverse. Students majoring in vehicle engineering have a basic theoretical understanding of battery systems but lack in-depth learning and programming skills; enterprise engineers have rich engineering practical experience but have insufficient understanding of cutting-edge data-driven diagnostic algorithms; learners with a computer science background are proficient in algorithms and programming but have weak knowledge of battery electrochemical mechanisms and engineering application scenarios. The common core demand of all learners is to master the complete ability chain of applying deep learning technology to battery fault diagnosis, to meet the industry's demand for compound talents. The main learning difficulties lie in the integration of interdisciplinary knowledge, understanding of complex algorithm principles, the threshold of programming practice, and obtaining high-quality real battery fault data for model training and validation.

Table 1. Analysis of the Profiles of Potential Learners of the Course

Learner types	Prior knowledge level (battery knowledge / deep learning / programming ability)	Core learning needs	Possible difficulties that may be encountered
Undergraduate student majoring in Vehicle Engineering	Basic / None / Advanced	Master the basic theories and design methods of battery systems.	Insufficient ability to integrate interdisciplinary knowledge
Engineer of New Energy Enterprises	Proficient / Basic / Proficient	Enhance the optimization skills of battery management systems	The implementation of real-time data processing algorithms is difficult.
Postgraduate student majoring in computer science	None / Proficient / Fluent	Learn battery modeling and simulation technology	Insufficient understanding of the electrochemical mechanism
Vocational training students	Basic / None / None	Practical skills required for obtaining industry certifications	Lack of engineering practice experience

4.2 Industry Competency Standards and Teaching Objectives

The development of the new energy vehicle industry places high demands on technical talents for battery maintenance. Industry standards stipulate that practitioners must hold a low-voltage electrician certificate, have undergone professional training and assessment, and possess specialized capabilities such as fault diagnosis. The overall goal of the course is to cultivate compound talents capable of applying deep learning technology to solve complex fault diagnosis problems of power batteries. The specific teaching objectives are divided into three dimensions: the knowledge objective is to master the principles of battery failure mechanisms (such as thermal runaway, etc.) and deep learning models (such as CNN, etc.); the ability objective focuses on battery data preprocessing, etc.; the quality objective emphasizes the cultivation of engineering ethics and other capabilities to address practical engineering challenges[7].

4.3 Overall Design Framework of the Course

The course design adheres to the concept of "theory-technology-practice-innovation" as a four-in-one approach, aiming to establish a progressive learning path from basic cognition to comprehensive innovation. It is recommended that the total class hours be 64, with the distribution of theoretical teaching, experimental teaching, and project practice in a ratio of 4:3:3 to ensure a close integration of theory and practice. The course content is designed in a modular format, divided into four logically progressive modules: the basic theory module (16 class hours) covers battery principles and the fundamentals of deep learning; the core technology module (20 class hours) delves into data-driven diagnostic methods and tools; the comprehensive practice module (16 class hours) trains system design and fault detection capabilities through real or simulated projects; and the frontier expansion module (12 class hours) introduces the latest industry trends and technology discussions. Through sequential teaching activities, each module systematically supports the achievement of the three-dimensional teaching goals of knowledge, ability, and quality, ultimately cultivating professional technical talents that meet the high standards of the industry.

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5. Teaching Content Design of Diagnosis Model based on Deep Learning

5.1 Design of Data Acquisition and Preprocessing Module

The performance of the battery fault diagnosis model is highly dependent on high-quality data. This module aims to guide students to understand the data sources, key parameters, and the preprocessing process. The data mainly come from four aspects: laboratory test platforms, real vehicle CAN bus data, public datasets, and simulation data. These data provide rich working conditions and aging scenarios for model training. Key monitoring parameters are the basis of diagnosis, mainly including single cell voltage, total voltage, charge and discharge current, temperature, and insulation resistance. Understanding the physical meaning of these parameters is a prerequisite for subsequent feature engineering. Raw data usually contain noise, missing values, and outliers, which must be preprocessed. The process includes:

(1) Data cleaning, such as using interpolation methods to handle missing values and identifying and removing outliers based on statistical methods or isolation forest algorithms;

(2) Data normalization/standardization, scaling parameters of different dimensions to a similar range to accelerate model convergence;

(3) Data slicing and windowing, dividing long time series data into fixed-length samples to meet the input requirements of deep learning models.

In fault diagnosis, normal samples far outnumber fault samples, leading to data class imbalance. Therefore, data augmentation techniques such as oversampling, undersampling, and generative adversarial networks need to be introduced. These techniques can enhance the model's ability to identify rare faults. In practice, students are required to use Python, load the given NASA battery dataset, visualize key parameters, and complete data cleaning, standardization, and simple balancing processing to prepare for subsequent modeling.

5.2 Principles of Building Deep Learning Diagnostic Models

This module delves into how to transform preprocessed data into samples suitable for input into deep learning models and dissects the mainstream network architectures. For battery time series data, two forms can be constructed: 1. Image samples, where data from multiple time series parameters within a fixed time window are arranged into a two-dimensional matrix; 2. Sequence samples, directly input as time series into recurrent neural networks. Taking the convolutional neural network (CNN) as an example, its structure is designed as follows: the input layer receives the preprocessed data matrix; the convolutional layer uses multiple filters to automatically extract local spatial features; the pooling layer performs downsampling, enhancing feature robustness and reducing parameters; the fully connected layer integrates high-level features; the output layer uses the Softmax or linear activation function depending on the task. CNNs are adept at capturing spatial correlations in sensor data.

Taking the Long Short-Term Memory (LSTM) network as an example, its gating mechanism can effectively learn the dependencies in long time series, making it highly suitable for predicting the remaining useful life of batteries or recognizing the temporal patterns of early faults. LSTM can remember the historical degradation trends of health status, thereby making more accurate predictions. To simultaneously utilize spatial and temporal information, a fusion model can be designed, such as CNN-LSTM: first, use the CNN layer to extract spatial features within each time window, and then input the feature sequence into the LSTM layer to learn the temporal evolution patterns. This architecture can more comprehensively describe the dynamic behavior of batteries.

Different models are suitable for different faults. For instance, stacked autoencoders can be used for unsupervised feature learning and early anomaly detection; CNNs are sensitive to faults based on instantaneous waveforms or image-like data; and LSTMs are good at predicting progressive degradation faults. In teaching, students should be guided to select models based on the fault mechanism[8].

ISSN: 2414-1895 DOI: 10.6919/ICJE.202604_12(4).0003

5.3 Model Training and Evaluation Methods

This module guides students through the process of training, optimizing, and evaluating models. First, it is necessary to rationally divide the dataset: typically, it is divided into training, validation, and test sets in proportion. For cases with limited data, k-fold cross-validation can be used to enhance the reliability of the results. The loss function guides the direction of model optimization. For fault classification tasks, cross-entropy loss is commonly used; for regression tasks such as RUL, mean squared error loss is employed. The optimizer is used to minimize the loss function and update the network weights.

The practical section will demonstrate the code flow for building models using TensorFlow or PyTorch frameworks, including: defining the network structure, loading data, setting the loss function and optimizer, writing the training loop, and saving the best model. Model evaluation requires a comprehensive set of metrics. For classification tasks, accuracy, precision, recall, F1 score, and confusion matrix are used; for regression tasks, root mean squared error, mean absolute error, etc. are applied. The meanings of these metrics need to be explained, for example, a high recall rate is particularly important for safety-critical fault detection. To enhance students' understanding of the "black box" nature of deep learning, model interpretability methods such as gradient-weighted class activation mapping (Grad-CAM) are introduced. Grad-CAM can visualize which regions of the input data a CNN focuses on when making decisions, for instance, whether the model's attention is concentrated on the period of abnormal and sudden changes in temperature sensor data when it classifies a fault as "overheating".

A comprehensive experimental section is designed, requiring students to select a fault type, use the provided battery dataset, and independently complete the entire process from data preprocessing, feature construction, model building, training and tuning to final evaluation. The final submitted experimental report should detail each step, parameter selection, analysis of experimental results, and visualization charts, and discuss the model's strengths and weaknesses as well as potential improvement directions.

6. Teaching and Case Implementation

6.1 Construction of Simulation Experiment Platform

To meet the teaching requirements of the course on fault diagnosis of power batteries for new energy vehicles, while taking into account cost and teaching effectiveness, this course proposes and builds a hybrid experiment platform of "software simulation + hardware-in-the-loop". This platform aims to provide students with a complete closed-loop learning experience from algorithm simulation, data generation to physical verification. The software simulation platform is the core of teaching and consists of three key components. Firstly, a high-fidelity lithium-ion battery electrochemical-thermal coupling model is built using MATLAB/Simulink, which can simulate the dynamic response of the battery under normal and various fault modes. Secondly, a deep learning development and training platform is constructed based on the Python environment, integrating TensorFlow or PyTorch frameworks, facilitating students to design models and verify algorithms. Finally, drawing on fault injection technology, a fault injection module is designed and integrated into the Simulink model, which can flexibly simulate typical faults such as internal short circuits, increased connection impedance, and sensor drift of the battery, thereby efficiently and controllably generating a large amount of labeled fault data, solving the problem of scarce and high-cost real fault data.

The hardware-in-the-loop experiment platform is used to verify the actual performance of the diagnostic algorithm. This platform is composed of a programmable DC power supply, a programmable electronic load, a data acquisition card, a battery management system simulator, and an industrial control computer, etc. Among them, the electronic load is used to simulate the actual working conditions of the vehicle and conduct dynamic charge and discharge tests. The battery voltage, current, temperature and other signals are collected in real time through the data acquisition card and input into the industrial control computer running the diagnostic algorithm, achieving online

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processing and diagnosis of real physical signals by the algorithm, completing the migration from "virtual data" to "physical verification". The platform management emphasizes modularity and openness, ensuring stable operation and supporting students' secondary development.

6.2 Typical Fault Diagnosis Teaching Case Design

Centering on the core fault modes of power batteries, this course has designed three teaching cases that progress from simple to complex. Each case follows a standardized process of "case background - problem definition - data preparation - model design - experimental analysis - conclusion discussion", and provides sample codes and datasets.

Case One: Early Diagnosis of Internal Short Circuit in Batteries Based on 1D CNN. This case focuses on the identification of micro-short circuits, which are precursors to battery thermal runaway. The teaching emphasis is on guiding students to understand how to automatically extract weak abnormal features from one-dimensional time series data such as battery terminal voltage and temperature difference using a one-dimensional convolutional neural network. Data under different short-circuit resistances are generated through Simulink fault injection to build the dataset. Students will design and train a lightweight 1D-CNN model, learn the impact of convolution kernel size and layer number on feature extraction, and compare it with traditional threshold methods to appreciate the advantages of deep learning in capturing weak features.

Case Two: Battery Capacity Degradation Prediction and SOH Estimation Based on LSTM. This case aims to enable students to master the time series prediction ability of battery health status. It focuses on explaining recurrent neural networks, especially the application of long short-term memory networks in handling the time series degradation law of battery capacity. Students need to extract capacity sequences from historical cycle data of batteries and construct input-output windows. By adjusting the number of hidden layer units and time steps of LSTM, they will observe the long-term prediction accuracy of the model for capacity decline trajectories and discuss the impact of working conditions such as temperature and rate on the generalization ability of the prediction model.

Case Three: Cross-Condition Battery Fault Diagnosis Based on SAE and Transfer Learning. This case addresses a more advanced application challenge, that is, the diagnosis problem when there is a significant difference in working conditions between training and test data. The teaching core is to introduce stacked autoencoders for unsupervised feature learning and transfer learning strategies. First, SAE is used to learn robust feature representations from a large amount of unlabeled, mixed-condition data. Then, the diagnosis model trained under a certain working condition is fine-tuned by adjusting the last layer or multiple layers to adapt to new working condition data. Through this case, students will deeply understand the impact of data distribution differences on model performance and master practical techniques for improving model generalization ability.

6.3 Organization and Implementation of Course Practice

The course practice adopts a "stepwise" organization model, divided into three stages: verification experiments, design experiments, and comprehensive projects, gradually enhancing students' engineering practice and innovation capabilities. Verification experiments closely align with theoretical teaching, where students follow detailed experimental guidelines to reproduce teaching cases on pre-built simulation platforms, familiarizing themselves with the entire process of data preprocessing, model training, and evaluation. Design experiments pose open-ended questions, such as "Optimize the CNN structure in Case One to improve diagnostic speed," requiring students to consult literature, independently design improvement plans, and verify them. Comprehensive projects represent the climax of the course, typically conducted in groups, with an example task description being "Develop a prototype system for battery fault diagnosis based on deep learning." This project requires the integration of data acquisition (or simulation), feature processing, intelligent diagnosis, and visual alarm modules to form a complete software and hardware solution.

In the implementation of project organization, student groups need to complete the proposal report, mid-term review, system implementation, and final defense. The role of teachers shifts from

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knowledge disseminators to project mentors and resource coordinators, responsible for providing technical consultation, coordinating experimental equipment, and guiding students in project management. The assessment criteria cover multiple dimensions including theoretical foundation, algorithm implementation, system integrity, teamwork, and innovation. Through this full-process, project-driven practice model, students not only deepen their understanding of fault diagnosis technology but also comprehensively exercise their ability to solve complex engineering problems.

7. Teaching Effectiveness Evaluation and Curriculum Optimization

7.1 Teaching Effectiveness Evaluation System

To scientifically assess the teaching effectiveness of the "Fault Diagnosis of New Energy Vehicle Power Batteries Based on Deep Learning" course, this course has established a diversified and full-process teaching evaluation system based on the Outcome-Based Education (OBE) concept. This system aims to break away from the traditional single assessment model that emphasizes knowledge over ability and results over process, and instead focuses on students' learning outcomes and ability attainment.

The evaluation system encompasses two major dimensions: formative evaluation and summative evaluation. Formative evaluation runs throughout the teaching process, with indicators including classroom interaction participation, quality of laboratory reports, project interim achievements, and group collaboration performance, aiming to dynamically monitor the learning process. Summative evaluation focuses on the final learning outcomes, including the final theoretical examination, the quality of comprehensive project completion, and the defense performance. Notably, this course has introduced an assessment scale to quantitatively score students' comprehensive application of knowledge, engineering practice ability, and innovative awareness. After the course concludes, feedback on the course content, teaching methods, and experimental platforms is collected through a questionnaire survey system to provide a basis for continuous improvement.

7.2 Course Continuous Improvement Strategy

Based on the assessment and analysis results, this course has established a dynamic closed-loop teaching quality improvement system of "evaluation - diagnosis - feedback - improvement - re-evaluation", and formulated the following continuous optimization strategies:

Firstly, optimize the course content and teaching methods. In the short term, introduce industrial-level battery fault datasets and cases of cutting-edge models such as Transformer to reduce the difficulty of theoretical understanding. In the medium term, fully promote project-driven teaching and explore the flipped classroom model, adding online Q&A and peer review sections. In the long term, plan to develop a modular online experimental platform and integrate virtual simulation resources.

Secondly, strengthen practical teaching and resource construction. Actively cooperate with new energy vehicle enterprises or battery manufacturers to jointly build internship bases and introduce real engineering problems as project topics. At the same time, encourage and guide students to participate in discipline competitions such as the "China University Students Formula Car Racing Competition" to promote learning through competition and effectively enhance innovative practical abilities. Build an open-source code library and dataset sharing platform for the course to promote the accumulation and inheritance of learning resources.

Finally, improve the closed-loop improvement mechanism. Systematically feed back the assessment results of each round of courses, especially the analysis data of the achievement of teaching objectives, to the revision of course objectives, the adjustment of teaching content and the optimization of assessment methods. Through continuous iteration, ensure that the courses always keep up with the cutting-edge of technological development and dynamically adapt to the demand for cultivating innovative and compound engineering talents in the context of new engineering.

Table 2. Priority and Implementation Time Planning Matrix of Course Optimization Measures

Categories of optimization measures	Description of specific measures	Expected implementation difficulty	Expected effect impact	Suggested implementation stage
Renewal of content	Introduce cases of cutting-edge models such as Transformer	Medium	High	Short period
Method improvement	Adopt project-driven teaching to replace the traditional lecture-based mode.	High	High	Medium-term
Practice reinforcement	Add practical training loops for industrial-level dataset analysis.	Low	Medium	Short period
Resource construction	Develop a modular online experimental platform	High	High	Long-term
Renewal of content	Integrate interdisciplinary knowledge (such as cognitive science + AI)	Medium	Medium	Medium-term
Method improvement	Establish a dynamic learning effect assessment and feedback system	Medium	High	Long-term

8. Conclusion

This research focuses on the demand of the new energy vehicle industry and the gap in talent cultivation, completing the course design and construction of "Fault Diagnosis of New Energy Vehicle Power Batteries Based on Deep Learning", aiming to cultivate new types of engineering talents. The main work and core achievements can be summarized in four aspects: First, the course positioning and objectives are clarified, enabling students to master the principles of power batteries, fault modes, and the application of deep learning models, and cultivating their ability to solve complex engineering problems. Second, a progressive content system is constructed, with "data - algorithm - system - application" as the main thread, integrating knowledge from multiple disciplines, from the analysis of operational data characteristics to the design of fault diagnosis systems. Third, a teaching plan that emphasizes both theory and practice is designed, planning progressive teaching cases and practical projects, and building a complete skill chain. Fourth, ideas for diversified teaching assessment and resource construction are proposed, establishing a multi-dimensional assessment system, and exploring the construction of a hybrid experimental platform. The characteristics and innovations of the course design are as follows: First, it has a forward-looking focus on technological intersections, integrating the frontiers of deep learning with engineering problems. Second, it emphasizes the entire process of engineering practice, covering the complete intelligent diagnosis process. Third, it pays attention to solving real industrial problems, connecting with actual fault diagnosis scenarios. This course design fills the gap in professional teaching, providing a knowledge system for students in related majors, and through the integration of industry and education, it can cultivate compound innovative talents and contribute to the development of the new energy vehicle industry.

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