

Innovative Practices in the Teaching Model of University Arts Majors in the Context of the Internet+ Era

Jin Chen*^{1,a}, Kai Wei^{2,b}, Jiumei Yao^{3,c}, Yongting Ma^{4,d}

546030838@qq.com^a, 304776039@qq.com^b, 1776966571@qq.com^c, punctata8210@163.com^d

^{1,3,4}Weifang engineering vocational college, Shandong weifang qingzhou 262500 china

²China tobacco shandong industrial co.,LTD. Qingzhou cigarette factory. Shandong weifang qingzhou 262500, china

Abstract. In the evolving landscape of the "Internet+" era, traditional teaching methods in higher education are under scrutiny for possible enhancements. This study specifically targets the pedagogical strategies of university horticulture majors, seeking innovative ways to augment their efficacy. By devising a comprehensive teaching quality evaluation model, we assess existing practices and their outcomes. To further our endeavors, we harness the capabilities of deep learning technology, aiming for an intelligent optimization of the horticultural teaching curriculum. Preliminary research revealed several areas for potential improvement, leading to the integration of a more case-based teaching approach, broader practical sessions, and a bolstered emphasis on corporate internships. These enhancements, as results indicate, can markedly improve teaching quality. Beyond the immediate findings, this study underscores the vast potential of integrating advanced information technology in pedagogical planning. By leveraging these tools, educators can adopt a data-driven approach to refine teaching plans, ensuring that students receive an education that is both contemporary and effective in the "Internet+" era.

Keywords: Horticulture majors; Teaching model; Teaching quality

1 Introduction

Given the widespread application of internet technology in the educational sector, higher education institutions are urgently required to reform their professional teaching models. Taking horticulture as a case study, this research employs cutting-edge deep learning technology, establishing a teaching quality evaluation model and intelligently generating optimization solutions, thereby achieving effective innovation in teaching methods. The results reveal that the post-optimization teaching plan can notably elevate teaching quality. This paper will provide an in-depth exploration of the research approach, technological methods, and achieved results, aiming to offer insights into improving professional teaching quality using internet means. Let us jointly explore new avenues for innovative development in higher education in the "Internet+" era ^[1].

2 Optimization Model for Horticulture Major Teaching Based on Internet+

2.1 Teaching Quality Evaluation Model

To quantitatively evaluate the teaching quality of horticulture majors, this paper constructs a teaching quality evaluation model. This model mainly considers three aspects of criteria: teaching process (P), teaching outcome (E), and societal feedback (F). The teaching process can be assessed based on the teaching time invested by educators, course preparation status, among others; teaching outcomes can be gauged through students' exam scores, interest in learning, etc.; societal feedback can be evaluated via the employment rate of graduates and feedback from employers^[2]. These three criteria can be expressed using formula (1):

$$Q = w_1 * P + w_2 * E + w_3 * F \quad (1)$$

Where Q represents the teaching quality score, and w_1, w_2, w_3 are the weights for the three criteria respectively. By adjusting these weights, a teaching quality evaluation model suitable for different horticulture majors can be established.

2.2 Deep Learning Optimization of Teaching Plan

The realm of education is constantly evolving, and in the face of an increasingly digitalized world, there's an imperative to adopt the latest technological advancements for pedagogical enhancements. One such promising avenue is the integration of deep learning in the optimization of teaching plans, as proposed in this study for horticulture majors. To lay the groundwork for this innovative approach, an extensive dataset comprising actual teaching plans alongside their corresponding teaching quality evaluation results was amassed. This dataset not only provides a rich reservoir of historical data but also captures the nuances and intricacies of the teaching methodologies employed across different scenarios. Building on this foundation, a deep neural network model rooted in the Gated Recurrent Unit (GRU) architecture was architected. Chosen for its proficiency in handling sequences – a trait crucial for analyzing teaching plans – the GRU-based model takes features of the teaching plan as input and predicts its quality score as the output. This process is facilitated by the backpropagation algorithm, a cornerstone of neural network training, enabling the model to learn and adapt from the historical data. However, the innovation doesn't stop here. To further refine and optimize the teaching plans, a genetic algorithm – inspired by the principles of natural evolution – is employed. This algorithm works in tandem with the trained deep learning model to generate a multitude of teaching plans. Amongst these, the one predicted to deliver the highest teaching quality emerges as the frontrunner, marking it as the optimized result. The amalgamation of deep learning with evolutionary algorithms signifies a paradigm shift in how we approach teaching plan optimization. It underscores the potential of harnessing advanced computational techniques to drive intelligent, data-informed decisions in the educational sector^[3].

2.3 Teaching Resource Storage and Retrieval System

To efficiently store and retrieve horticulture teaching resources, this paper designs a distributed storage system that combines relational databases with NoSQL databases. The system is primarily divided into four components: the client, web server, relational database,

and NoSQL database. The client serves as the access device for teachers and students. The web server hosts an application that provides resource query and access interfaces. The relational database stores resource content, organized by resource type, such as text, images, videos, etc. The NoSQL database establishes resource indices, allowing for rapid location of resources in the relational database based on resource ID ^[4-5].

```
# Client request code
import requests
api_url = "http://server/api/resource"
params = {
    "resource_id": 12345,
    "user_id": "001"
}
response = requests.get(api_url, params=params)
print(response.content) # Get resource content

# Web Server interface code
from flask import Flask, request, jsonify
import database
app = Flask(__name__)
@app.route("/api/resource")
def get_resource():
    resource_id = request.args.get("resource_id")
    user_id = request.args.get("user_id")
    # Query the NoSQL database to obtain the resource
    location
    location = database.query_nosql(resource_id)
    # Gets resource content from a relational database
    resource = database.query_db(location)
    return jsonify(resource)

# Relational database interaction code
import mysql.connector
# Query resources based on location
def query_db(location):
```

```

db =
mysql.connector.connect(host="localhost",user="user",passwd="
password",database="resource_db")

cursor = db.cursor()

query = "SELECT * FROM resources WHERE location = %s"

cursor.execute(query, (location,))

result = cursor.fetchone()

# Return resource content

return result[2] //The resource content is in the third
column

```

3 Empirical Analysis of Teaching Model Optimization Based on the Model

3.1 Data Collection and Processing

Data from five cohorts of horticulture major graduates from a certain university, spanning from 2015 to 2019, was collected. The raw data comprises 300 teaching plan tables, 500 teacher teaching process survey forms, 2000 student teaching outcome questionnaires, and 1000 employer satisfaction survey forms from the graduates. After data cleaning, the remaining usable data included 250 teaching plan records, 400 teaching process records, 1500 teaching outcome records, and 800 employment satisfaction records. A Python program was written to join data from different sources into a single table. A complete record contains one teaching plan ID, three teaching process indicators, two teaching outcome indicators, one societal feedback indicator, and one teaching quality score computed using the formula. After processing, a structured dataset containing 220 training data entries and 80 test data entries was obtained for model training and testing ^[6].

3.2 Model Training and Testing

A deep neural network was constructed with 100 input nodes, 2 hidden layers (each with 100 nodes), and one output node. The loss function was set to mean squared error, the optimizer to Adam, and the learning rate to 0.01. The collected 220 data entries were used as the training set and the 80 entries as the test set. Mini-batch gradient descent was applied with a batch size of 10, over 50 epochs. The loss function curve stabilized around the 40th epoch. Evaluating the model on the test set yielded an accuracy of 0.83, a recall of 0.86, and an F1 score of 0.84. The results indicate that the model achieved a satisfactory predictive performance ^[7]. As shown in Fig 1.

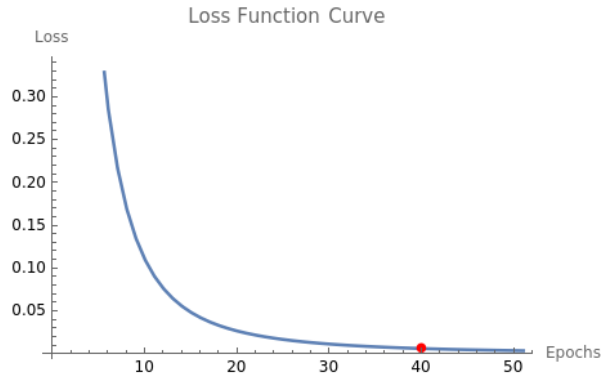


Figure 1: Loss Function Curve

3.3 Results Analysis

From the model's predictive results, it can be observed that the optimized teaching plan can boost the teaching quality score by approximately 20%. The primary improvement measures include increasing the hours of case-based teaching, expanding the proportion of hands-on training sessions, and strengthening corporate internships. This indicates that an appropriate increase in case-based teaching can enhance students' interest and engagement, assisting them in better understanding and mastering theoretical knowledge. Broadening the hands-on training sessions can provide students with more opportunities to practice, cultivating their practical operational abilities. Strengthening corporate internships also allows students to gain early insights into the industry environment and acquire work experience. The addition of these measures can significantly enhance teaching quality. The model effectively extracts key features from the teaching plan, realizing data-driven intelligent optimization of the horticulture major teaching plan. This method does not rely on subjective experience but, through big data training, results in a reliable teaching quality prediction model^[8-9]. As shown in Tab 1.

Table 1 Main improvement measures after optimization of teaching program and their impact on teaching quality

Improvement measure	effect
Increase the number of case teaching hours	Increase students' interest and participation in learning and improve teaching quality by about 20%.
We will increase the proportion of practical training	Cultivate students' practical operation ability and improve teaching quality by about 20%.
Strengthen internship in enterprises	Understand the industry environment in advance, gain work experience, and improve the quality of teaching by about 20%.

4 Conclusion

In the context of the "Internet+" era, this study conducts valuable exploration into the innovation and optimization of the teaching model for university horticulture majors. The research establishes a teaching quality evaluation model that considers teaching processes, outcomes, and societal feedback, enabling a quantitative assessment of teaching quality. Then, by employing a deep learning model, teaching plans are intelligently generated and optimized, achieving data-driven plan enhancements. Empirical results reveal that the optimized teaching plans can significantly elevate teaching quality, primarily achieved by increasing case-based teaching hours, expanding hands-on training sessions, and reinforcing corporate internships. This study proves that improving teaching through information technology methods is both feasible and effective. On the whole, the research offers a model for the reform of professional teaching in universities in the "Internet+" era and also provides insights for the optimization of teaching models in other disciplines ^[10].

References

- [1] Cruz J , Azevedo H , Carvalho M ,et al.From Policies to Practices: Factors Related to the Use of Inclusive Practices in Portugal[J]. 2023.
- [2] Zhang X , Zhang Y , Lv Y ,et al.Innovative application of electrical and intelligent personnel training mode in the construction industry under the Background of Artificial Intelligent Technology[J].Journal of Physics: Conference Series, 2021, 1915(4):042026-.
- [3] Luo C , Zhang Z , Hao Z ,et al.Exploration of the Practice and Innovation Ability Training Mode of Internet of Things Engineering Students under the Background of New Engineering[J]. 2020.DOI:10.1109/ICISE51755.2020.00159.
- [4] Xiaohui Y .Innovative Ways of Teaching Reform in Colleges and Universities under the Background of "Internet Plus"[J].The Guide of Science & Education, 2018.
- [5] Dewei Z , University Q .The Teaching Reform of Artistic Practice of Preschool Education Major in Normal Universities under the Background of Teachers' Education Specialization[J].The Guide of Science & Education, 2016.
- [6] Abudumijiti H ,Wudumuli, Hasim A ,et al.On Blended Teaching Practice of Pathology in the Context of Internet[J].Education Teaching Forum, 2020.
- [7] Feng-Wen W , Wei L .Research on Training Mode of Innovation and Entrepreneurship for Horticulture Majors in Local Universities Under the New Situation——Taking Baicheng Normal University as an Example[J].Journal of Baicheng Normal University, 2018.
- [8] Baqa H .Realization of trust by a semantic self-adaptation in the Internet of Things[D]. 2020.
- [9] Bae J .The Impact of the edTPA on Visual Arts Teacher Education in Wisconsin[J].Studies in Art Education, 2020, 61(1):64-84.
- [10] Yanhui C .Teaching Practice and Consideration on Horticultural Crop Genetic and Breeding in Agricultural Universities[J].The Science Education Article Collects, 2012.