

A Knowledge–Competence–Value Integrated Teaching Framework for Neural Networks and Deep Learning

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Abstract—With the increasing application of artificial intelligence (AI) in manufacturing, healthcare, transportation, and public services, the educational objectives of the Neural Networks and Deep Learning course are shifting from algorithmic knowledge and programming skills toward broader AI competence. Existing courses usually provide a systematic foundation in neural network theory, model architectures, training methods, and programming practice, but the connections among knowledge acquisition, problem-solving competence, and responsible technology use remain insufficient. This limitation has become more evident with the rapid development of Transformers, generative AI, and large language models, which require students not only to implement models but also to analyze data, compare solutions, interpret results, identify risks, and evaluate appropriate use. This study proposes a Knowledge–Competence–Value (KCV) integrated teaching framework. Knowledge provides the conceptual foundation, competence reflects the ability to apply knowledge to complex problems, and value concerns technological goals, responsibilities, risks, and broader impacts. Technical practice serves as the connecting mechanism among these dimensions. A teaching process of problem context, knowledge construction, technical practice, result analysis, competence development, and responsible judgment is proposed, together with implementation strategies involving project-based learning, generative AI integration, and diversified assessment. The framework aims to support a transition from model-centered teaching toward comprehensive and responsible AI education.

Keywords—Neural networks and deep learning; artificial intelligence education; teaching reform; problem-solving competence; AI literacy; responsible AI.

I. INTRODUCTION

Deep learning has become a fundamental component of contemporary artificial intelligence. With continuous advances in computing power, data availability, and algorithmic methods, deep neural networks have expanded from image classification, speech recognition, and natural language processing to industrial inspection, medical image analysis, intelligent transportation, environmental monitoring, and automated decision-making. Convolutional neural networks, deep neural networks, and Transformer architectures have substantially advanced representation learning and sequence modeling and have also provided the technical foundation for recent developments in generative AI [1-3]. These changes have expanded the scope of AI applications while simultaneously increasing the expectations placed on university-level AI education.

The Neural Networks and Deep Learning course is commonly offered as a core course in artificial intelligence, computer science, data science, and related programs. It combines mathematical and algorithmic foundations with strong engineering characteristics[4]. Students are generally expected to understand artificial neurons, activation functions, loss functions, gradient descent, backpropagation, and regularization, while also learning representative models such as CNNs, RNNs, LSTMs, attention mechanisms, and Transformers. In addition, they need to use deep learning frameworks to perform data preprocessing, model construction, optimization, and evaluation. The course therefore serves as an important bridge between basic algorithmic learning and more advanced AI system design.

At the same time, the goals of higher education are increasingly shifting from knowledge acquisition alone toward the integrated development of knowledge, competence, and responsible professional judgment. China's Outline for Building a Leading Country in Education (2024–2035) emphasizes strengthening the role of higher education in talent development and technological innovation [5]. UNESCO's AI Competency Framework for Students similarly integrates AI knowledge, application, creation, human-centered perspectives, and ethical responsibility, highlighting the importance of evaluating AI outputs, impacts, and appropriate uses[6]. These changes suggest that AI-related courses should assess not only whether students understand models and can implement algorithms, but also whether they can analyze problems, interpret evidence, and make appropriate technical decisions.

However, current Neural Networks and Deep Learning courses are often organized around a sequence of basic theory, representative models, algorithm implementation, and experimental verification. This structure supports systematic knowledge delivery, but it can also encourage students to focus primarily on formulas, network reproduction, and performance improvement. Students may successfully train a CNN on a predefined dataset while still lacking the ability to independently analyze data characteristics, compare model architectures, select evaluation metrics, or diagnose failure cases. Programming implementation and complex problem-solving competence are therefore not equivalent.

The rapid development of generative AI has made this problem more visible. Large language models can now support concept explanation, code generation, debugging, and academic writing, thereby changing how students acquire

knowledge and complete learning tasks. Existing studies suggest that generative AI can enhance information access, personalized learning, and feedback, while also raising concerns regarding overreliance, academic integrity, privacy, and the possible reduction of higher-order cognitive engagement [7-12]. If assessment continues to emphasize only final code, standard answers, or predictive performance, it becomes increasingly difficult to determine whether students have genuinely engaged in reasoning, verification, and technical decision-making.

In addition, the suitability of an AI system for real-world use cannot be judged by predictive accuracy alone. Data representativeness, class imbalance, reliability, computational cost, error consequences, and human oversight may all affect deployment decisions. For example, a model with high average accuracy may still be unsuitable for medical diagnosis or industrial safety if it performs poorly on critical classes. Students therefore need to understand not only how to construct models, but also how to evaluate their applicability and potential consequences.

To address these challenges, this study proposes a KCV integrated teaching framework for the Neural Networks and Deep Learning course. In this framework, knowledge provides the conceptual foundation for understanding AI technologies, competence reflects the ability to transfer knowledge to new problems, and value refers to the ability to consider technological goals, engineering responsibility, risks, and broader impacts. Technical practice connects the three dimensions. Based on this framework, the study analyzes current teaching limitations, constructs a three-dimensional objective system, and proposes corresponding curriculum and implementation strategies.

II. KEY PROBLEMS IN CURRENT TEACHING

Although the course generally contains substantial theoretical and practical content, the relationships among different learning outcomes remain insufficiently integrated. Three problems are particularly important.

2.1 Knowledge Is Systematic but Often Insufficiently Problem-Oriented

Current courses usually cover the major models and algorithms of deep learning in a relatively complete sequence. However, teaching often emphasizes definitions, formulas, and architectures rather than the problems that motivated them. Students may understand how backpropagation is calculated without fully connecting it to optimization, or reproduce a CNN without explaining why convolution and weight sharing are suitable for image data. A stronger problem-oriented structure can help students understand not only what a model is, but why it was developed and under what conditions it is useful. This provides a better foundation for knowledge transfer and later model selection.

2.2 Programming Practice Does Not Automatically Produce Complex Problem-Solving Competence

Programming laboratories are essential, but many are highly structured. When the dataset, architecture, and key code

are already provided, successful implementation mainly demonstrates procedural competence. Higher-order learning requires students to analyze, evaluate, and create rather than only remember and apply[13]. Active learning research similarly shows that problem analysis and inquiry support deeper learning[14]. Therefore, practical tasks should gradually move from model reproduction to parameter comparison, error analysis, model selection, and open-ended problem solving.

2.3 Responsible Judgment Is Not Fully Embedded in Technical Activities

Privacy, fairness, safety, and academic integrity are increasingly discussed in AI education, but these topics are often separated from model design and evaluation. In practice, many responsibility-related issues emerge directly from technical processes. Class imbalance can lead to unequal performance, false negatives may create safety risks, and generative AI hallucinations can affect information reliability. AI literacy research has emphasized that technical understanding and social or ethical judgment should be considered together [15, 16]. Accordingly, students should be encouraged to analyze the consequences of model behavior when those consequences are relevant to real-world use.

III. THE KNOWLEDGE–COMPETENCE–VALUE FRAMEWORK

The KCV framework treats knowledge, competence, and value as connected rather than parallel learning outcomes. Knowledge supports understanding, competence supports problem solving, and value supports responsible technical judgment.

3.1 Knowledge: From Content Coverage to Structured Understanding

Students should master core concepts such as activation functions, loss functions, backpropagation, CNNs, RNNs, LSTMs, attention mechanisms, and Transformers. However, these concepts should be organized through their problem relationships. For example, nonlinear activation can be introduced through the limitation of the perceptron, convolution through the inefficiency of fully connected networks for images, LSTM through long-term dependency problems, and Transformers through the limitations of sequential computation. This organization helps students form a more coherent professional knowledge structure.

3.2 Competence: From Model Reproduction to Problem Solving

Competence should include data analysis, model selection, training design, error diagnosis, result interpretation, and solution comparison. These abilities should be developed progressively, beginning with guided implementation and moving toward open-ended problem solving. Importantly, model quality should not be judged only by a single accuracy score. Students should learn to compare stability, class-specific performance, efficiency, and other task-relevant factors.

3.3 Value: From General Principles to Evidence-Based Technical Judgment

The value dimension focuses on how students evaluate the appropriateness and consequences of technical choices. It should be grounded in actual model evidence rather than detached discussion. For example, students may need to decide whether a high-accuracy model with poor recall on critical samples is suitable for deployment, whether a larger model is justified by marginal performance gains, or whether generative AI outputs require independent verification. In this way, responsible judgment becomes part of technical reasoning.

IV. INTEGRATING KCV INTO COURSE CONTENT

The KCV framework can be embedded directly in the core modules of the course rather than added as a separate component. The main design is summarized in Table 1.

TABLE 1. KCV integration across course modules

Course module	Knowledge focus	Competence focus	Value and responsibility focus
Data processing	Data splitting, normalization, augmentation, class balance	Data analysis and diagnosis	Data quality and fairness
Neural network fundamentals	Perceptron, activation, loss, backpropagation	Mechanism analysis	Scientific reasoning
CNN	Convolution, pooling, feature extraction	Model design and comparison	Reliability and safety
RNN/LSTM	Sequence modeling, long-term dependency	Model selection	Privacy and applicability
Model evaluation	Accuracy, Precision, Recall, F1	Error and risk analysis	Professional responsibility
Transformer	Self-Attention, multi-head attention, positional encoding	Knowledge transfer	Critical use of technology
Generative AI	Pretraining and generation	Output verification	Integrity and information responsibility

4.1 From Model Understanding to Engineering Judgment

In neural network fundamentals, teaching can begin with model limitations. For example, failure of a single-layer perceptron on XOR can be used to motivate multilayer networks and nonlinear activation. Similarly, backpropagation can be introduced as a solution to the problem of parameter optimization rather than as an isolated mathematical derivation. In CNN teaching, students can compare architectures in an industrial defect detection task. Instead of focusing only on overall accuracy, they can analyze false negatives, Recall, and F1-score for critical defect classes. This shifts the learning task from “Which model performs best?” to “Which model is most appropriate for the application?”

4.2 From Data Processing to Data Responsibility

Class imbalance provides a useful example of KCV integration. Students can compare overall accuracy and class-specific recall, then apply class weighting or data augmentation to improve performance. When minority classes are interpreted as high-risk samples, students can further

evaluate whether unequal performance is acceptable. This approach allows fairness and responsibility to emerge directly from model behavior rather than from abstract discussion.

4.3 From Generative AI Use to Output Verification

Generative AI can be incorporated through “generate–verify–revise” tasks. Students may use a large language model to generate code, explanations, or experimental conclusions, but they must verify the outputs using course knowledge. Research suggests that the educational effectiveness of generative AI depends strongly on verification, reflection, and task design [17, 18]. Therefore, the key learning objective should be the ability to judge generated content rather than simply produce it.

V. IMPLEMENTATION STRATEGIES

The effectiveness of the KCV framework depends on how teaching activities are organized. Three strategies are particularly important.

5.1 Problem-Driven Learning

A teaching sequence of problem context, knowledge explanation, technical practice, result analysis, and judgment can connect the three dimensions. For example, before introducing Precision and Recall, students can be asked whether a disease screening model with 99% accuracy is necessarily reliable. This creates a meaningful context for learning evaluation metrics and discussing different error consequences.

5.2 Progressive Project-Based Learning

Practical tasks can progress from structured experiments to open-ended projects. Early exercises support basic understanding, intermediate tasks emphasize comparison and diagnosis, and later projects require students to analyze data, select models, justify design choices, and evaluate applicability. An industrial defect detection project, for instance, can require students to report not only accuracy but also critical-class recall, model complexity, and the need for human review.

5.3 Assessment Aligned with the KCV Objectives

Assessment should evaluate more than final model performance. Constructive alignment theory emphasizes consistency among learning outcomes, activities, and assessment[19]. Knowledge can be assessed through conceptual understanding, competence through projects and error analysis, and value through scenario-based technical judgment. Formative feedback should also be included because it helps students identify gaps and improve their work [20]. When generative AI is allowed, students can be asked to document key interactions and explain how generated outputs were verified.

VI. CONCLUSION

As AI systems increasingly enter complex engineering and

social contexts, the Neural Networks and Deep Learning course should move beyond model knowledge and programming skills toward broader problem-solving competence and responsible technical judgment. The rapid development of generative AI further strengthens the need to reconsider teaching and assessment practices centered on standard answers and final code. UNESCO has similarly emphasized human agency, privacy, safety, and responsible AI use in educational settings[21]. This study proposed a Knowledge–Competence–Value integrated teaching framework. Knowledge provides the conceptual basis for understanding AI, competence supports the transfer of knowledge to new problems, and value supports evidence-based judgments about risks, responsibilities, and applicability. Technical practice connects the three dimensions.

The proposed framework does not require a separate value-education module. Instead, responsible judgment is embedded in data analysis, model evaluation, project work, and generative AI use. Through problem-driven learning, progressive projects, and aligned assessment, students can move from simply building and training models toward explaining model behavior, comparing technical alternatives, and evaluating whether AI systems are appropriate for specific contexts. This approach provides a practical direction for the reform of AI-related university courses.

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