# LEARNING EXPERIENCE TRANSFER SYSTEM ARCHITECTURE WITH ARTIFICIAL INTELLIGENCE ENGINEERING

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**ABSTRACT**

Most studies of the learning transfer process involve considering the transfer of academic results or credits from studies between institutions or programs. This is challenging because individual experiences are abstract. Each person's experiences must be transferable, that is to say, concrete, and tangible for use as information, allowing institutions to proceed with the transfer process and raise the level of one's career. Therefore, this article aims to design the architecture of the learning experience transfer system using an artificial intelligence engineering process. Learning experiences occur concerning each person and are transferred to learning experiences using text pre-processing. Text pre-processing consists of six steps: Step 1, Text cleaning; Step 2, Tokenization; Step 3, Lexical analysis; Step 4, Stop words; Step 5, Semantic analysis; and Step 6, Finding the weight of words, i.e., the importance of words (Keyword), using the TF-IDF method to find the weight of each word. Then, similarity values are found to compare the similarities between learning experiences and professional competency levels. Finally, the research takes and stores the learning experience in a knowledge-based manner. The experimental results showed that the Random Forest algorithm had the highest predictive value with Accuracy equal to 100%. This outstanding performance underscores the potential of the Random Forest algorithm in our proposed learning experience transfer system, instilling confidence in its effectiveness and reliability. When the system architecture was designed and evaluated by experts, the results showed the highest level of appropriateness.

**Keywords:** *Learning experience, Artificial intelligence engineering, Machine learning, Text pre-processing*

## 1. INTRODUCTION

Learning experience transfer involves applying knowledge and skills acquired in one context to new situations, enhancing both personal and professional development. This concept has been explored across various domains. Each context provides unique insights into how learning transfer can be optimized and applied effectively. In educational settings, recreational activities have been shown to facilitate learning transfer. Students perceive that skills and concepts learned through such activities apply to future courses and life situations, emphasizing the importance of experiential learning in education. A study by Elizabeth Vargas Vera et al. also identified specific activities instrumental in developing transferable skills, highlighting the role of well-designed educational programs in promoting learning transfer [1]. Carter et al. propose the TOTALS Capstone model in business education integrates team-based learning with individual applications, mirroring corporate training practices. This approach fosters collaboration and self-awareness, enabling students to transfer skills effectively from training to situations demonstrating individual success. The model emphasizes the importance of understanding one's learning style, which can enhance the ability to transfer knowledge and skills across different contexts [2]. Roig-Ester et al. propose a study of new nursing professionals highlighting previous work experience's impact on learning transfer. Nurses with substantial academic preparation and self-competence demonstrated higher learning transfer, suggesting that both educational background and self-efficacy are crucial for effective knowledge application in the workplace. The interaction between previous work experience and learning transfer was significant, indicating that practical experience can enhance the ability to apply theoretical knowledge in real-world settings [3]. Rohr et al. present control systems and experience transfer, focusing on designing robust controllers that can adapt to variations across different systems. This approach ensures that controllers are effective across a heterogeneous fleet, demonstrating the potential of experience transfer in technical fields. Using scenario optimization and data-driven control methods allows for developing controllers that generalize well, even with limited data, showcasing the efficiency of experience transfer in engineering applications [4] [5]. Michael J. Sorocky et al. propose Learning experience transfer in robotics through a data-efficient algorithm that estimates similarity between robot systems. It highlights the importance of selecting appropriate experiences from source robots to avoid negative transfer. By utilizing a similarity metric inspired by the ν-gap from robust control theory, the authors demonstrate that informed experience selection can significantly enhance the learning process. Their experiments with quadrotors show a 62% performance improvement when experiences are chosen based on this similarity metric [6]. Yu et al. study the TrCart and TrAdaBoostCart algorithms leverage transfer learning to enhance user experience (UX) modeling, particularly in small sample sizes. By transferring knowledge from related tasks, these algorithms improve the accuracy of UX predictions and uncover meaningful relationships between UX, user characteristics, and software factors. The study demonstrates that the TrAdaBoostCart algorithm yields superior accuracy and interpretable results, providing valuable insights for designing mobile applications and enhancing user satisfaction [7]. Kittiviriyakarn et al. propose five main components that predict the transfer of professional experience: Qualifications, Conditions, Knowledge, Assessment Methods, and Professional Standards. These components have been analyzed to understand their impact on the transfer process. A model for professional experience transfer is created by integrating intelligent portfolio predictions with service agents. This model includes three main components: Import Data, Process, and Results. The intelligent service agent plays a crucial role in filtering and searching for information based on the criteria for professional experience transfer [8]. While these studies highlight the benefits of learning experience transfer, challenges remain in ensuring that the transfer is effective across diverse contexts. Factors such as individual differences, the complexity of the new environment, and the nature of the skills being transferred can influence the success of learning transfer. Understanding these variables is crucial for optimizing learning experiences and ensuring that the knowledge and skills obtained are effectively applied in new situations.

Thailand has established a professional qualification system through the Professional Qualification Institute [9]. This system is designed to enhance human resources, catering to both users and the production sector while certifying individuals' capabilities according to professional standards to meet the demands of the business and industrial sectors. The system facilitates the transfer of learning experiences for individuals with work experience or those who can demonstrate learning through various forms of evidence, including certificates, work videos, portfolios, and follow-up interviews. Experts from professional qualification institutions conduct assessments. However, there are several challenges associated with this assessment method, as the evaluators may allow personal emotions or physical conditions, such as feeling unwell, to influence their judgments, potentially compromising the accuracy of the assessment results. To address this issue, the author proposes utilizing a learning experience transfer system architecture incorporating artificial intelligence engineering that delivers consistent and acceptable assessment outcomes for all stakeholders.

This article is organized as follows: Part 2 presents a literature review of the topic, examining related theories and research. Next, the Methodology section provides detailed information on the research methods used. Then, the Research Results are presented, followed by the Discussion. Finally, in the Conclusion, the author reviews this article's main content and outlines possible directions for future research.

## 2. LITERATURE REVIEW

The author collected relevant concepts and theories by studying and analyzing documents and research related to this research topic. The details are as follows:

### 2.1 Learning Experiences

Learning experiences are related to interactions, curricula, programs, living conditions, social environments, physical environments, and facilities. A consideration of the context that makes up the learning environment includes using instrumentation, models, experiments, data analysis, design, learning from failure, creativity, mentality, safety, communication, teamwork, research ethics, sensory perception, and experience. Other factors that impact learning or directly influence a person's experience in education are also included. The objective is to help learners have better access to their learning experiences [10][11][12]. Transfer learning aims to extract knowledge from a related

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task called the source task in such a way as to improve the prediction model of the attempted learning task or the target task. For transfer learning to be implemented and knowledge transfer to be successful, there must be a shared basis between the source and target tasks. For example, the curriculum is often the same in education, but students and teachers may change [13]. Learning experience equivalency includes interactions, curriculum, living conditions, social environment, physical environment, facilities, atmosphere within the learning environment, and tools to measure the learning experience. The objective is to extract knowledge from related work upstream to improve downstream work.

### 2.2 Artificial Intelligence (AI) Engineering

Artificial Intelligence (AI) Engineering is a rapidly evolving field that integrates AI technologies into software development, aiming to address unique challenges and opportunities. This field is reshaping traditional software paradigms by incorporating AI-specific methodologies and ethical considerations. AI Engineering encompasses various aspects, including the development of AI-based systems, collective intelligence, and the role of AI in scientific advancements. Key features of AI Engineering include: AI has revolutionized predictive maintenance and fault detection by analyzing extensive datasets to predict equipment failures, thus minimizing downtime and enhancing system reliability [14]. In the power sector, AI aids in effective planning, operation, and control, offering novel approaches to efficient evaluation and decision-making [15]. The AI engineering process for predictive analytics involves five phases: requirements analysis, design, implementation, testing and verification, and prediction and maintenance. This structured approach combines machine learning and software engineering to develop robust predictive models [16].

### 2.3 Text Pre-Processing

Text preprocessing is a fundamental step in natural language processing (NLP) that involves cleaning and transforming text data to make it suitable for analysis. This process is crucial for improving the performance of various NLP tasks such as text classification, sentiment analysis, and topic modeling. The main components of text preprocessing include normalization, tokenization, stemming, lemmatization, and stop-word removal. These steps help reduce noise, correct typos, and standardize word usage, thereby enhancing the quality of the input data for further analysis. Text Preprocessing Methods are discussed as follows: tokenization, the process of splitting text into individual words or tokens, which is fundamental for many NLP tasks. Precise tokenization can enhance the accuracy of parts-of-speech tagging and other downstream tasks [17][18]. Text normalization, including converting text to lowercase and correcting misspellings, helps reduce variability in the text data, which can improve model performance [19][20]. Removing stopwords (common words such as "and" and "the") and punctuation can reduce noise in the data, making it easier for models to focus on meaningful content. However, the impact of these steps can vary depending on the dataset and the specific NLP task [19][21]. Stemming and lemmatization reduce words to their base or root forms, which can help consolidate different word forms into a single representation. This is particularly useful in tasks such as text classification and sentiment analysis [17][20]. Creating n-grams (combinations of n consecutive words) and identifying multiword expressions can capture context and improve the performance of models in tasks such as machine translation and reasoning [17][18]. Text preprocessing is a crucial step in preparing textual data for analysis, particularly when using the Term Frequency-Inverse Document Frequency (TF-IDF) method. TF-IDF is a statistical measure used to evaluate the importance of a word in a document within a collection of documents. Effective text preprocessing enhances the quality of TF-IDF representations, which in turn improves the performance of various text analysis tasks such as clustering, classification, and information retrieval. The following sections outline key text preprocessing techniques and their impact on TF-IDF [22][23].

## 3. METHODOLOGY

The author proceeded to design the architecture of the learning experience transfer system using AI Engineering. In accordance with the AI Engineering process [16], the design process consists of five phases: Phase 1: Requirements analysis, Phase 2: Design, Phase 3: Implementation, Phase 4: Testing and Verification, and Phase 5: System Development and Maintenance.

**Phase 1 Requirements Analysis**

In this step, the goal is to transfer individual practitioners' learning experiences in AI Engineering. The author will collect data on personal learning experiences from a group of computer professionals derived from their work experiences. This data will be derived from their work experiences. The next step involves improving data

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quality, managing missing data, encoding it, and categorizing it. These processes are summarized in Table 1 below.

*Table 1: Information on transfer of learning experiences.*

| Professional competency level information (Thailand Professional Qualification Institute, 2021) | Learning experience information (personal learning experience) |
|---|---|
| 1. Qualification Pathways Data<br>1.1 Education qualifications (education level, field of study)<br>1.2 Work experience information (number of years worked, job position) | 1. Personal Data<br>1.1 Education (education level, field of study)<br>1.2 Work experience information (number of years worked, job position) |
| 2. Performance criteria<br>Detail of performance criteria | 2. Detailed learning experience<br>Course description, job description |
| 3. Digital professional competency level<br>System developer Level 3,<br><br>Computer and computer system<br>Service provider Level 3,<br><br>Data engineer Level 4,<br>Information systems security manager Level 4,<br>Network and computer security management Level 5 | 3. Person's occupation such as: System developer, System analysis and design etc. |

This study investigates professional skill levels within the digital industry [9], focusing on a dataset that includes five specific roles: Systems Developer Level 3, Computer and Computer Systems Service Provider Level 3, Data Engineer Level 4, Information Systems Security Manager Level 4, and Network and Computer Security Manager Level 5. The goal of data collection is to enable individuals with relevant experience to compare their own experiences against these five professional skill levels.

**Phase 2 Design**

The process of designing a learning experience transfer WORD MISSING? involves comparing each individual's learning experience with the appropriate professional competency level. To achieve this, it is important to assess the qualifications and work experience of the transferee. Additionally, the details of the learning experience, such as course descriptions and job descriptions, should be evaluated against the performance criteria. Since these performance criteria are expressed in text, natural language processing (NLP) techniques can be applied to determine the significance of keywords. This process consists of six steps:

*Step 1: Text cleaning* – This involves reducing data by removing punctuation marks, numbers, and extra spaces and replacing repeated punctuation marks, emojis, and emoticons.

*Step 2: Word segmentation* – This step divides or segments words correctly according to grammatical rules.

*Step 3: Lexical analysis* – Here, we check the grammatical structure of various word groups that make up a sentence and compare these words with a dictionary.

*Step 4: Stop word removal* – In this step, we eliminate common words that often appear in sentences or documents but do not contribute to the overall meaning or characterization of the text.

*Step 5: Semantic analysis* – This step involves verifying the correctness of the sentence and conducting a semantic evaluation.

*Step 6: Keyword extraction* – The author determines the significance and importance of words (keywords) using the Term Frequency-Inverse Document Frequency (TF-IDF) method to convert them into a TF-IDF vector.

The TF-IDF vectorization equation determines the importance of words. Details are given in an equation [24][25][26] as follows:

$$\text{Weight} = tf * idf \tag{1}$$

The value of TF is found from the formula:

$$tf(t,d) = \frac{\text{The number of words included in the document}}{\text{The number of words in the total document}}$$

TF (t, d) is the number of occurrences of "t" in document "d".

t is a term or word.

d is that document.

The determination of IDF can be obtained from the formula:

$$IDF(t) = (\log N / dfi + 1)$$

t is a term or a word.

N is the total number of words contained.

Df (t) is the number of documents found for the term t.

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The entire process of transferring learning experiences is illustrated in Figure 1.

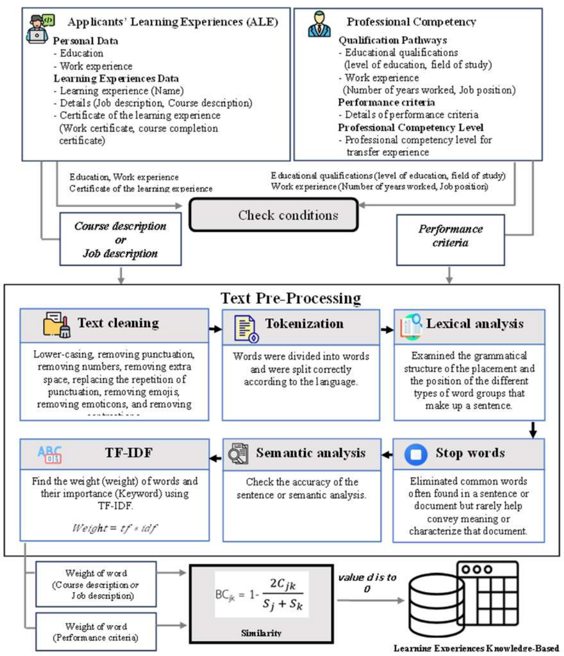


*Figure 1: Process of Learning Experience Transfer*

This study compares learning experiences by predicting digital professional abilities using supervised learning algorithms in a group of classifications: decision trees, naive Bayes, KNN, and random forests. It collected the learning experiences of 30 people with work experience in the digital industry. The data was divided into two parts: training data and testing data. The Bray-Curtis distance equation was used to measure the differences [27][28].

$$BC_{jk} = 1- (2Cjk)/(Sj\ + Sk\ ) \qquad (2)$$

$BC_{jk}$ is the word that refers to the difference in the transfer of learning experience.

$C_{ik}$ is the sum of the smaller numbers of the individual words.

$S_j$ is the total number of words counted from the learning experience corpus.

$S_K$ is the total number of words counted from the Learning Experience.

This formula results in a value between 0 and 1, where 0 indicates identical composition, and 1 indicates complete dissimilarity.

For further efficiency, the keywords with similar weights between the learning experience description and the performance criteria are stored in Learning Experience Knowledge-Based.

**Phase 3 Implementation and Phase 4 Testing and Verification**

The model's performance was evaluated using 10-fold cross-validation with the aid of RapidMiner, using separate training and testing datasets. To measure the accuracy of academic achievement prediction, precision, recall, and the F-measure, the training dataset was tested on the testing dataset. The equations for precision, recall, and F-measure [29][30][31] are as follows.

$$Precision = TP/(TP+FP) \qquad (3)$$

$$Recall = TP/(TP+FN) \qquad (4)$$

$$Accuracy = (TP+TN)/(TP+FP+FN+TN) \qquad (5)$$

$$F\text{-}Score = 2\times Precision\times Recall)/(Precision+Recall \qquad (6)$$

TP is the amount of data that was correctly extracted.
FP is the number of erroneous data extracted.
TN is the amount of valid data that was not extracted.
FN is the number of erroneous data that has yet to be extracted.

The efficiency test results in terms of decision trees, naive Bayes, KNN, and random forests algorithms are as follows. The Naive Bayes algorithm has precision-recall and F-score values divided according to professional competency levels from learning experiences. System developer level 3 (SD L3) has a Precision score equal to 100, a Recall score equal to 95.65, and an F-score equal to 97.78. The computer and Computer System Service provider (CSS L3) has a Precision score of 93.75, a Recall score of 100, and an F-score of 96.77. Information Systems Security Manager Level 4 (ISSM L4) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Data Engineer level 4 (DE L4) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Network and Computer Security Management Level 5 (NCS L5) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100.

The K-Nearest Neighbor (KNN) algorithm has precision-recall and F-score values divided according to professional competency levels from learning experiences. System developer level 3 (SD L3) has a Precision score equal to 100, a Recall score equal to 95.65, and an F-score equal to 97.78. Computer and Computer System Service provider (CSS L3) has a Precision score equal to 93.75, a Recall score equal to 100, and an F-score equal to

96.77. Information Systems Security Manager Level 4 (ISSM L4) is valuable: the Precision score equals 100, the Recall score equals 100, and the F-score equals 100. Data Engineer level 4 (DE L4) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Network and Computer Security Management Level 5 (NCS L5) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100.

The Random Forest algorithm has Precision, Recall, and F-score values divided according to professional competency levels from learning experiences. System developer level 3 (SD L3) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Computer and Computer System Service provider (CSS L3) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Information Systems Security Manager Level 4 (ISSM L4) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Data Engineer level 4 (DE L4) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Network and Computer Security Management Level 5 (NCS L5) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100.

The decision tree algorithm has precision-recall and F-score values divided according to professional competency levels from learning experiences. System developer level 3 (SD L3) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Computer and Computer System Service provider (CSS L3) has a Precision score equal to 100, a Recall score equal to 93.33, and an F-score equal to 96.55. Information Systems Security Manager Level 4 (ISSM L4) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Data Engineer level 4 (DE L4) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100. Network and Computer Security Management Level 5 (NCS L5) has a Precision score equal to 100, a Recall score equal to 100, and an F-score equal to 100.

Table 2 shows the Precision, Recall, and F-score values for predicting digital professional competency. It can be explained as follows.

*Table 2: Precision, Recall, and F-Score values for predicting digital professional competencies.*

| **Algorithm Prediction** | | **Professional Competency Level** | | | | |
|---|---|---|---|---|---|---|
| | | System Developer Level 3 *(SD L3)* | Computer and Computer System Service Provider *(CSS L3)* | Information Systems Security Manager Level 4 *(ISSM L4)* | Data Engineer Level 4 *(DE L4)* | Network and Computer Security Management Level 5 *(NCS L5)* |
| Naive Bayes | Precision | 100 | 93.75 | 100 | 100 | 100 |
| | Recall | 95.65 | 100 | 100 | 100 | 100 |
| | F-Score | 97.78 | 96.77 | 100 | 100 | 100 |
| K-NN | Precision | 100 | 93.75 | 100 | 100 | 100 |
| | Recall | 95.65 | 100 | 100 | 100 | 100 |
| | F-Score | 97.78 | 96.77 | 100 | 100 | 100 |
| Random Forest | Precision | 100 | 100 | 100 | 100 | 100 |
| | Recall | 100 | 100 | 100 | 100 | 100 |
| | F-Score | 100 | 100 | 100 | 100 | 100 |
| Decision Tree | Precision | 100 | 100 | 100 | 100 | 100 |
| | Recall | 100 | 93.33 | 100 | 100 | 100 |
| | F-Score | 100 | 96.55 | 100 | 100 | 100 |

The experimental results indicate that the Random Forest algorithm has the highest accuracy value, at 100%. Next is the Decision Tree, with an accuracy value of 98.89%. Naive Bayes and KNN have an accuracy value of 98.75%. Accuracy in predicting digital professional competencies, therefore, uses the Random Forest algorithm as a model to develop a system for transferring learning experiences. This result is shown in Table 3.

*Table 3: Accuracy in predicting digital professional competencies*.

| Algorithm | Naive Bayes | KNN | Random forest | Decision Tree |
|---|---|---|---|---|
| Accuracy | 98.75 % | 98.75 % | 100.00 % | 98.89% |

**Phase 5 System Development & Maintenance**

The performance test results indicate that the Random Forest model exhibits the highest performance. Consequently, this model is utilized to design the system architecture in the next section.

## 4. RESULTS

For results of Learning Experience Transfer System Architecture with Artificial Intelligence Engineering**,** Figure 2 below shows that the architecture of the AI engineering learning experience transfer system includes two components: component one, the user (the experience transfer requestor), and component two, data management and AI engineering. The user experience transfer includes information such as education level, field of study, and work experience, including years of experience and job positions. It also covers learning experiences, detailing job titles or course names and, provides comprehensive descriptions of jobs or courses. Additionally, it provides information on certificates, including employment verification or course completion certificates.

The data management and AI engineering part has five steps as follows:

**Step 1 Requirements analysis:** Requirements analysis involves data collection, preliminary data processing, and feature selection.

**Step 2 Design:** Design selects an algorithm to compare learning experiences and predict professional competency levels. It can be detailed as. A text pre-processing process with six steps: Step 1: Text cleaning, Step 2: Token generation, Step 3: Lexical analysis, Step 4: Stop words, Step 5: Semantic analysis, and Step 6: Find the weight of words using the TF-IDF equation. The weight of each word about each ability will be used to obtain the resource for learning experiences. Therefore, the information from people with work experience is used to transfer learning experiences. If the learning experiences are similar, they will be stored in the Learning Experience Knowledge-Based as a learning resource and tested to find algorithms for prediction, including decision trees, naive Bayes, KNN, and random forests in the prediction process.

**Step 3 Implementation and Step 4 Testing and Verification:** Develop the system using the Random Forest algorithm, which has been tested by comparing it with other algorithms and found to be the most efficient for this task.

**Step 5 System Development & Maintenance:** Develop, implement, and maintain the system.

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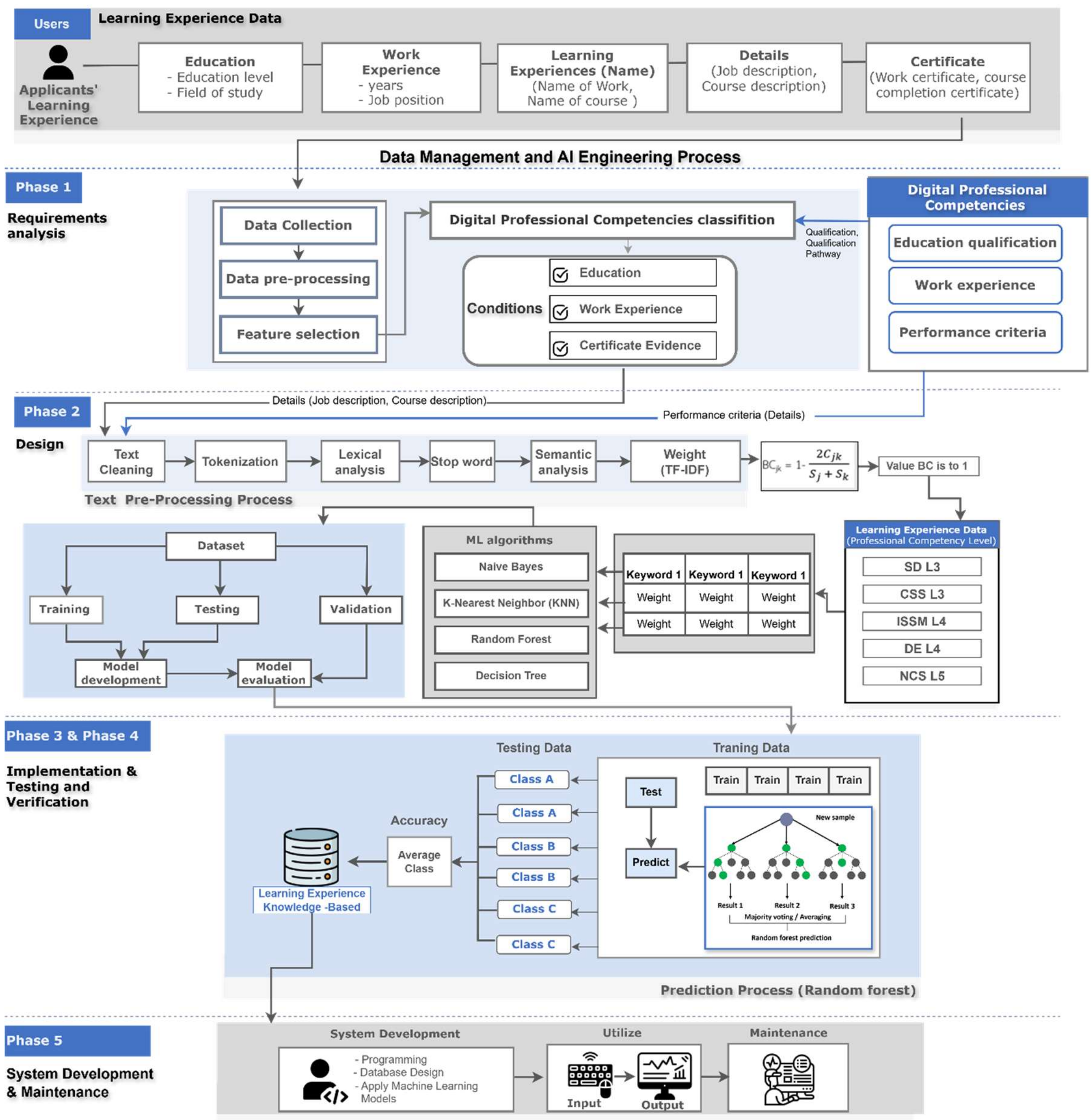


*Figure 2: Learning Experience Transfer System Architecture with Artificial Intelligence Engineering*

The assessment of the suitability of the Learning Experience Transfer System Architecture with Artificial Intelligence Engineering by 20 experts in artificial intelligence working in the digital industry is summarized as follows. Table 4 shows the evaluation results of the Learning Experience Transfer System Architecture with Artificial Intelligence Engineering. The overall average of the evaluation results was found to be at the highest level of appropriateness (Mean = 4.95, SD = 0.11).

*Table 4: The suitability assessment of Learning Experience Transfer System Architecture with Artificial Intelligence Engineering.*

| *Assessment List* | *Evaluation Results* | | |
|---|---|---|---|
| | *Mean* | *S.D.* | *Results* |
| **1. Users or those requesting transfer of learning experiences** | | | |
| 1.1 Students (currently studying for a bachelor's degree) | 4.60 | 0.89 | Very good |
| 1.2 Those working in a professional career | 5.00 | 0.00 | Very good |
| **2. Information for learning experiences transfer** | | | |
| 2.1 Personal Data<br>2.1.1 Educational information | 5.00 | 0.00 | Very good |

| *Assessment List* | *Evaluation Results* | | |
|---|---|---|---|
| | *Mean* | *S.D.* | *Results* |
| 2.1.2 Work experience information | | | |
| 2.2 Learning Experiences Data<br>2.2.1 Name of the learning experience<br>2.2.2 Learning experience details or learning experience completion certificate data | 5.00 | 0.00 | Very good |
| **3. Input device** | | | |
| 3.1 Keyboard | 5.00 | 0.00 | Very good |
| 3.2 Mouse | 5.00 | 0.00 | Very good |
| **4. Data management and AI Engineering Process** | | | |
| 4.1 Transfer data through the server. | 4.80 | 0.45 | Very good |
| 4.2 Check the conditions. | | | |
| 4.2.1 Education | 5.00 | 0.00 | Very good |
| 4.2.2 Work experience | 5.00 | 0.00 | Very good |
| 4.2.3 Certificate evidence | 5.00 | 0.00 | Very good |
| **5. Process** | | | |
| 5.1 Text Pre-Processing | 5.00 | 0.00 | Very good |
| 5.1.1 Text cleaning | 5.00 | 0.00 | Very good |
| 5.1.2 Tokenization | 5.00 | 0.00 | Very good |
| 5.1.3 Lexical analysis | 5.00 | 0.00 | Very good |
| 5.1.4 Stop word | 4.80 | 0.45 | Very good |
| 5.1.5 Semantic analysis | 5.00 | 0.00 | Very good |
| 5.1.6 Weight of TF-IDF | 5.00 | 0.00 | Very good |
| 5.2 Prediction with Random Forest Algorithm | 4.80 | 0.45 | Very good |
| **6. Output device** | | | |
| 6.1 Web Application | 5.00 | 0.00 | Very good |
| 6.2 Smartphone | 5.00 | 0.00 | Very good |
| 6.3 Tablet | 5.00 | 0.00 | Very good |
| **Overall average score in all aspects** | **4.95** | **0.11** | Very good |

## 5. DISCUSSION

Table 3 shows the results of the Random Forest algorithm's performance test, indicating an accuracy of 100%. In comparison, Naive Bayes has an accuracy of 98.75%, KNN has an accuracy of 98.75%, and Decision Tree has an accuracy of 98.89%. Due to its inherent design and flexibility, the Random Forest algorithm is well-suited for handling high-dimensional data and correlated features. It employs an ensemble of decision trees, each trained on a random subset of features, which helps manage the data's complexity and dimensionality. This approach reduces overfitting and allows the algorithm to capture complex feature interactions—the algorithm's ability to provide variable importance measures further aids in identifying and managing correlated features. Consistency with theoretical analyses has shown that Random Forests can adapt to high-dimensional settings, maintaining consistency even with complex, nonparametric regression functions. This adaptability is achieved through a bias-variance decomposition analysis, which characterizes how Random Forests' bias depends on factors such as sample size and tree height [32][33]. This is consistent with the data used for testing because the professional competence level has related data characteristics. At the professional competence level, it consists of several sub-competencies similar to the structure of a Random Forest. Random Forests are composed of multiple decision trees and hierarchical models that split data into subsets based on feature values to make predictions [34] [35]. Learning Experience Transfer System Architecture with Artificial Intelligence Engineering achieved the highest level of expert evaluation because the AI Engineering process is straightforward, combining the concept of the AI process with the software engineering process [16]. All five processes are easy to maintain when the system is completed, allowing up-to-date improvements and fixes, making it ready for use at all times.

## 6. CONCLUSION

This article involves designing the architecture of a learning experience transfer system using artificial intelligence engineering processes. This system aims to make individual learning experiences transferable and concrete for career advancement purposes. The study highlights the effectiveness of the Random Forest algorithm in predicting professional competency levels based on learning experiences. The algorithm achieved a precision, recall, F-score, and accuracy of 100%, demonstrating its potential for use in the proposed system. The conclusion also suggests that the system's architecture can significantly enhance the transferability of learning experiences, making them more tangible and valuable for individuals seeking to improve their professional competencies. Future studies are likely to explore further enhancements to the system architecture and investigate additional machine learning algorithms that could improve the system's performance and applicability across different domains. This article implies that future research could also expand the dataset and test the system in various real-world scenarios to validate its effectiveness and reliability in diverse settings. This article is limited because it can only predict knowledge derived from work experience or training experience. Experts who analyze performance videos or demonstrations must evaluate the performance aspect. Such evaluations may require advanced image processing techniques, which need further development.

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