Artificial intelligence (AI) is a hot topic in various industries, including the IT industry. AI is going beyond research in self-driving cars and robot intelligence, already coming into use in familiar areas such as automatic translation on the Internet and in games such as computer shogi and chess.

Meanwhile, Japan is facing a serious problem of a labor shortage in many industries as the country has already entered an era of declining population. JR East is entering a period of mass retirement of veteran engineers in the area of maintenance, so securing maintenance engineers and passing down skills into the future are becoming major issues. As one way to overcome these issues, we started research on ability to use AI technology, which is seeing tremendous advancement, as part of maintenance work support. This paper will introduce case examples of work support application of AI, which we are working on as part of the Smart Maintenance Initiative1).

2.1 History of AI 2) 3)

The word “artificial intelligence” was first used in 1956 in a workshop held by Dartmouth College in the USA. The advance of AI has not been without setbacks, though, as seen in the two periods of slowdown in Fig. 1. Early AI involved research in substituting human thinking with rule-based programs. However, there were limits to substituting human thinking with rules, so AI research waned and entered its first period of slowdown.

Later, in the late 1970s, research increased in expert systems where the knowledge and experience of experts are transferred to computers. However, those expert systems too were fundamentally rule-based, so they went out of use due to their inflexibility, resulting in the second period of slowdown in AI research.

The concept of big data later came about in the mid 2000s with the advancement of the Internet and rapid improvement in computer performance. In 2011, IBM’s Watson, which implemented the mechanism of machine learning, defeated human opponents on a TV game show and the Siri voice recognition software became standard on iPhones, bringing AI more into the public view. In 2012, Google used the new technology of deep learning to successfully identify pictures of cats on the Internet. With those achievements, we have exited the second period of slowdown and entered the third AI boom.

Today’s AI, unlike rule-based types before, uses machine learning to enable a computer to recognize features from large volumes of data. Deep learning is technology that enables a computer to autonomously obtain those features by machine learning. In other words, while AI of the past involved humans taking much time to comprehensively decide rules, now it can be used in a variety of venues as long as there is a database where knowledge and applications of skills are accumulated. That means new maintenance methods utilizing AI technology can be created if a large volume of data related to maintenance is available.

2.2 Classification of AI

There are many ways of thinking regarding classification of AI, but it can be classified into the three types shown in Fig. 1, for example, 4) 5) The features of the three types are as follows.
3. Support for Passing Down Maintenance Skills Using AI

Studies were conducted to find out how AI classified into the aforementioned three types can each be used for railway maintenance work and to find out if there are issues in use of AI. The following covers the results of those studies.

3.1 Question Answering Type AI

The data used by question answering type AI is text information. Reports are prepared regarding inspections in day-to-day maintenance work and when troubles occur, and the company holds much text data on various recording media. For example, when failures occur with wayside facilities, the progress and cause of those is recorded in reports. We believe it may be possible to develop a system where, using that information, advice is given to maintenance workers according to failure type by having the system recognize them using machine learning. In other words, the system must be able to extract data and knowledge related to failures and perform inference without error.

From the research we found the need to obtain a certain amount of data and minimize variation in language. Facilities do not fail often, so we need to consider how to secure data on at least 10,000 incidents. Variation in language goes beyond differences in capitalization and phrasing, and we need to consider differences in how things are called by different departments and abbreviated names as well. Minimizing the variation in language also impacts the accuracy of inferring the causes of facility failures, so much time has to be spent in this task.

3.2 Pattern Recognition Type AI

The data used by pattern recognition type AI is image information. In this paper, we introduce as an example the results of research on a work support method that uses image information.

Currently, track facility monitoring devices are installed on trains in operation on the Yamanote Line and other JR East lines to monitor the day-to-day condition of track. Those monitoring systems obtain numerical data on track warping and capture image information on the rail surroundings (Fig. 3). We built a prototype system that uses those images of around the rail (two-dimensional gray-scale images) to detect defects on the surface of rails and classify them according to type using AI technology (Fig. 4).

The rail surface condition classification system extracts faults on the rail surface that can be discerned when observing images by the human eye. Faults extracted are classified as “head checks”, “corrugation”, “squat”, and “other defects”. This system is characterized in that rail surface defect images are classified according to failure type by having the system recognize them using machine learning. In other words, the system must be taught features of defect images as preparation before classification. After that, images obtained by monitoring and input to the system are classified into the four types of defects and their locations are displayed in a list.

Evaluating use of the system to detect defects with data of part of a particular line, we found that it was able to classify head checks at a detection rate of 95%. However, there was misdetection (detection of defects that should not have been judged to be defects) at a rate of 3%, confirming the system could not achieve the feature of AI whereby classification of quality can be done without error.
From previous research, we know that judgment cannot be made well if there is not enough data to be learned as defects and if the condition of defects that can be classified changes due to re-learning when results of classification by the system are poor. In other words, with a system that uses machine learning, defects that maintenance engineers want to find according to the condition of their own areas can be set.

3.3 Optimization/Judgment Type AI
As mentioned in section 3.1, JR East has accumulated a large amount of inspection data. The majority of that is data that can be expressed numerically or ranked. One example of numerical data is track warping expressed in a chart as in Fig. 3. Other data includes results of repair work and facilities data showing the types of facilities. We studied whether or not we could find new knowledge from that large volume of data (big data), using AI.

Fig. 5 shows the flow of AI calculation used in the research. We studied a system where AI finds correlations from large volumes of explanatory variables (data of explanatory tables) that humans cannot analyze for a particular objective (data of objective table) and presents the results most closely associated. Maintenance engineers consider the work-related significance of those results using know-how derived from experience, and we expect for them to be able to apply that to work as new knowledge.

The following introduces two case examples of analysis using this AI. First is an example of analysis of factors behind track deterioration of local lines. Table 2 shows the results found by AI based on numerical data expressing track structure and status of deterioration as accumulated in commonly used systems. The greatest factor provided by AI on track deterioration was sections having a mixture of wooden and concrete sleepers in a ratio of 35% to 51%. This matches empirical impressions. The second greatest factor—curve radius being 5,700 m or greater—expresses straight sections. The target local line had much straight track, which is probably why we obtained such results. In this way, the results found from AI require human thinking to determine their significance.

The next case example uses data of a different local line where we studied the effects of wooden and concrete sleepers on maintenance costs. Data input included repair expenses and type of sleeper. Fig. 6 shows the results of analysis. The vertical axis is the ratio of annual repair expenses with those per 100 m for wooden sleeper track expressed as 100, and the horizontal axis shows the ratio of concrete sleepers in a 100 m section. As shown in the graph, repair expenses drop greatly at concrete sleeper ratios of 17% and 70%. This is a case example that numerically demonstrates that annual maintenance expenses can be reduced by changing the material for sleepers from wood to concrete.
From these results, we believe that in the future we will be able to use AI to make maintenance work more efficient. To do so, however, we need to accumulate much maintenance data.

**4 Issues in Utilizing AI**

The main objectives of formulating systems for railway maintenance were to computerize recording work done by humans and to reduce human error in judgment work. In other words, to clearly express “yes” and “no” by switching from analog to digital. However, it had previously been impossible to substitute railway maintenance know-how (tacit knowledge of veteran engineers, for example) with computers. That is also the reason why it has proven difficult to conduct maintenance by inexperienced engineers relying on computers. AI may be able to make up for lack of ability to make decisions in maintenance work from non-numeric know-how and the like, but there are still many issues to overcome in order to achieve that. The following summarizes what we have found in research up to now.

1. **Centralization of data scattered throughout the company**
   Much data is required in order to utilize AI. For that reason, we need an environment where data scattered throughout various systems can be gathered and used in a centralized manner. Additionally, a data map is needed where the location of data can be seen at a glance.

2. **Data storage assuming switch to IoT**
   Switching to IoT for monitoring and other inspections requires handling of large volumes of images and other data. We therefore need to promptly put in place items such as storage methods and the networks where data is exchanged.

3. **Variation in terms by department**
   In order to handle text information, terminology used in railway maintenance must be minimized. A dictionary that can unify the railway terms that differ by department must be put in place, and entry items and entry support methods must be thought up.

4. **Necessity of thinking maintenance**
   AI is a tool that derives solutions for content learned the same as is done by humans. In other words, humans must decide what AI is to learn, and solutions AI comes to are not necessarily 100% correct. Some vagueness will always remain, just as there is with human memory. In order to utilize AI, we maintenance personnel too must think for ourselves and use AI upon correctly understanding its characteristics.

**5 Conclusion**

In this paper, we introduced from a perspective of maintenance support what will happen when utilizing AI, referencing case examples of research. AI analyzes large volumes of information in a short amount of time—a task that humans cannot handle—and presents those results as solutions. Those solutions may present us with new perspectives that we hitherto had not noticed, and those must be put to use in maintenance. In other words, AI holds promise in greatly changing maintenance as a process called experience engineering. Therefore, we intend to keep a close eye on the future advancement of AI.

**Reference**

1. Head checks
   Rail surface damage where fine cracks form over a wide area that tends to occur mainly on the outer rail of curved sections

2. **Corrugation**
   Continuous scale-like wear that occurs mainly on the inner rail of curved sections

3. **Squat**
   Rail surface damage with dark depressions that occurs mainly on straight sections

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