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AI-based Electric Fire Detection State Judgment Data Set Construction

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Abstract: In this paper, we create a virtuous cycle ecosystem of AI data for judging electric fire status. Data collection reflects feedback on inspection results such as collection of electric fire status judgment data through cloud sourcing and purification, processing, inspection and data disclosure of the collected data. It is necessary to determine the cause of the damage through fire forensics in order to confirm the property damage caused by the fire. The damage investigation so far is based on the experience of the investigator, and it is difficult to conduct a sufficient investigation and analysis of multiple fires. Accordingly, by building a data set for AI learning for the cause analysis of electric fires, The AI composition that can overcome the subjective and unprofessionalism of the forensic of electric fires is made. Therefore, we study the reliability and system development feasibility of digital conversion of fire detection report and data for AI learning.

Keywords: 1st dragon mark; 2nd dragon mark; cause of fire; electric fire; electrical fire causes; fire detection; melt marks

1 INTRODUCTION

The digital conversion of the fire status survey report and its use as data for AI learning (fire occurrence, dispatch date, fire location, cause, ignition-related equipment, damage situation, weather situation, etc.). It reminded us of the importance of fire forensics to check fire property damage [1]. In case of electrical accidents such as electric overload, trekking, compression damage, insulation breakdown, and short circuit, the metal is melted by arc or Joule heat and then re-solidified molten traces occur [2].

There are two types of melt marks: the primary short-circuit marks generated by a short circuit after the wire coating is lost, and the secondary short-circuit marks generated by the short circuit after the wire coating is lost due to the heat of a fire. And after melting by the heat of fire, the molten trace solidified again is called a fissure trace [3, 4]. It is absolutely necessary to establish an electric fire-related data set to identify the ignition point and cause of such a fire site.

In response to the need to apply AI for fire detection, fire forensics analyzes the cause of an accident, and can be used as basic data in various ministries such as the police, insurance, firefighting, and safety and disaster centers. In the case of CCTV, which can reveal the cause of the fire, it is damaged in case of fire or is not installed inside the house, so it has a low possibility of use [5]. To overcome this limitation of manpower, fire detection using AI is needed. The areas of interest for each subject of fire detection are different, providing fire detection data from various perspectives and remotely performing fire detection, overcoming the limitations of fire detection personnel and effectively managing disaster situations [6].

To promote the policy of expanding the application of intelligent information technology in in response to the 4th industrial revolution, the basic plan for national digital transformation through intelligence is established and the scale of the national informatization field for ICBM (IoT, Cloud, Bigdata, Mobile) related technologies is continuously expanding. Accordingly, data set construction requires a large amount of manpower and time for large-large-scale data collection. In addition, in order to expand the application of cutting-edge technology for the identification of the cause of fire, the vision for building AI/big data, future radiance, and governance and the realization of a disaster safety digital platform were made. In addition, the digital conversion of the fire investigation report and its use as data for AI learning (fire occurrence, dispatch date and time, fire location, cause, ignition-related equipment, damage situation, weather situation, etc.)

Fire-related property damage continues to increase from 2011 to 2020, and the amount of damage is close to 600 billion won as of 2020. In order to classify victims only by identifying the cause of damage through fire forensics, it is necessary to identify the cause in other fields, such as the police and insurance, in addition to firefighting. The fire investigation so far is a method based on the experience of investigators, and it is difficult to sufficiently investigate and analyze many fires.

Therefore, in this paper, the construction of the state judgment data set for the AI-based electric fire detection is designed in Chapter 2 the construction of data for AI learning and the refinement work In Chapter 3, we analyzed the state of scars and traces for data acquisition, and in Chapter 4, we developed an AI data utilization model.

2 RELATED WORKS

2.1 Building Data for AI Training

2.1.1 Electric Fire Status Judgment Data

From 2011 to 2020, the occurrence of electric fires accounted for 20%. The limitation of the fire-related data management system is that only statistical data disclosed by the National Fire Agency through the National Fire Information System are provided, so there is a limit to the use of artificial intelligence [6]. In the case of fire detection, it plays an important role not only in firefighting-related fields, but also in insurance, police, and fire recovery [7]. In particular, a high- level objective/reliable analysis report is required when the payment of damage recovery costs is determined according to fire detection.

2.1.2 Building Data for Artificial Intelligence Learning

In the data construction environment for artificial intelligence learning, a data set construction system is used as shown in Fig. 1 for data collection, electrical fire status determination data labeling, and data set utilization [8]. By accumulating the experimental data of the 1st dragon mark, the 2nd dragon mark, and the fissure, it builds a data set to provide a solution by building a system that can determine the cause of a short circuit through Ai-based situation recognition/judgment. Build an electric fire cause analysis system using AI as a data set for AI learning. The cause of fires occurring in these various environments is excluded from errors that occur depending on the individual ability of the monitor, and the results of the inspection are presented with high objectivity. It is for the development of a fire detection service that enables smooth progress of administrative services such as insurance related to recovery after an accident by quickly analyzing the cause of the accident.

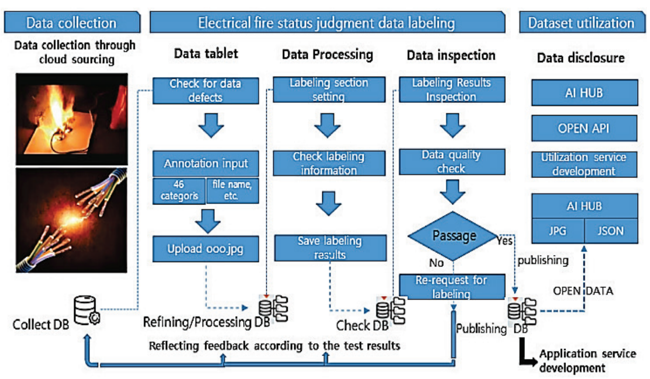


Figure 1 Dataset construction system

A data set is built by classifying electrical related short circuits that occur in the event of a fire in the fire situation data into fire causes (primary dragon marks) and non-fire causes (secondary dragon marks, heat marks). Digital conversion work is carried out by securing the wire deformation form of 5 types of wires can be mainly identified at the fire site as raw data.

2.2 Raw Data Collection Method

Raw data is collected through electric fire generating equipment as shown in Fig. 2.

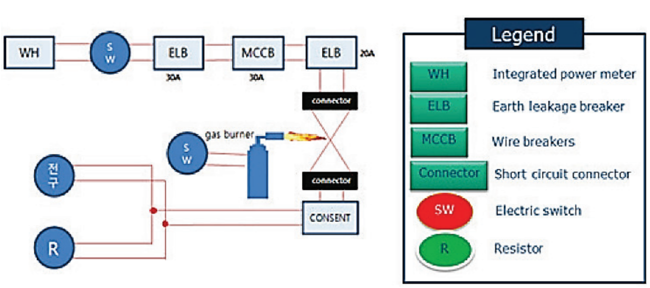


Figure 2 Electric fire generating equipment

The short circuit of the first melting mark is tested at room temperature and at a high temperature ranging from about 2,000 to 6,000 °C at the moment of short circuit. This causes a phenomenon in which the surface of the metal is melted in an instant, and the short-circuited part is scattered or the power is cut off. Here, the experiments are collected using the generation equipment under safe and standardized experimental conditions [9].

2.3 Raw Data Purification

It utilizes cloud based data storage that can collect and store large-scale data. A distributed development environment software development tool that enables collaboration in a distributed environment is used.

A computer system capable of processing multimedia using stable high-speed Internet/infranet capable of sending and receiving large amounts of data is required [10, 11].

To strengthen data transmission efficiency, cloud sourcing is applied and a system that can be transmitted quickly on the web is built. After reading the image stored in the server to the PC, it creates JSON and saves only JSON to improve work efficiency. In this data purification process, clear data purification standards are established according to the purpose of data construction, data types, and domain characteristics. In the refining step, after setting the objects required for data labeling, the data is refined according to the standards required for data for artificial intelligence learning [20]. Data purification uses tools (software) and applies methods such as exclusion or transformation according to set rules, and methods of visually checking and inspecting data by the operator [12, 13, 19].

The quality measurement standards that occur in the process of inspecting the purification and labeling results are somewhat emotional and subjective for each individual. A clear result that an individual inspector can be sure of is marked ○, and even a slightly unclear result is marked with △, and the final quality evaluation is requested by an expert. The evaluation results of experts are immediately fed back to individual inspectors, so that inspectors can share the evaluation criteria of experts and maintain consistent quality measurement standards in the future [14].

3 DATA ACQUISITION

3.1 Generation of Raw Data by Primary Dragon Marks

The primary short-circuit marks are melt marks that occurred before the fire or that the insulation material was damaged due to a fire and then short-circuited. When an electric short occurs, a large current of 2,000 A to 3,000 A is generated and high-temperature heat is generated. Although a fire can be caused by a spark generated by a short circuit, the current flows back and damages electrical equipment and equipment. Install an earth leakage breaker and a circuit breaker after the primary power switch to install safety equipment so that the breaker operates immediately when a large current occurs.

For the primary short circuit scar generation method, apply commercial power (220 V, 60 Hz) as shown in Fig. 3.

In a situation where loads (light bulbs and electrical facilities) are connected, an electrical short circuit (SHORT CIRCUT) is generated by artificially shorting the + and - lines between the electrical short connectors. At this time, the generated molten wire is used as raw data [15].

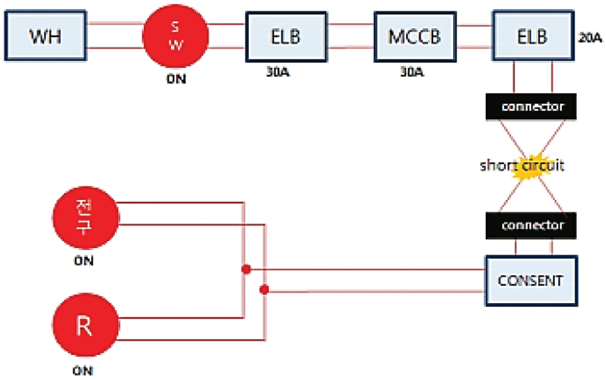


Figure 3 Primary dragon trace generation equipment

3.1.1 Data Acquisition by Primary Short Circuit

Fig. 4 is the raw data generated by collecting the primary short circuit traces that lead to fire when the wiring sheath is short-circuited due to insulation deterioration or physical external force.

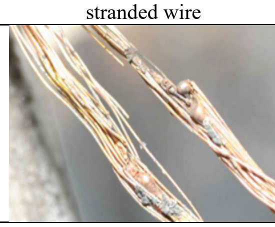
1st short circuit	
1 line	stranded wire
	

Figure 4 1st dragon mark

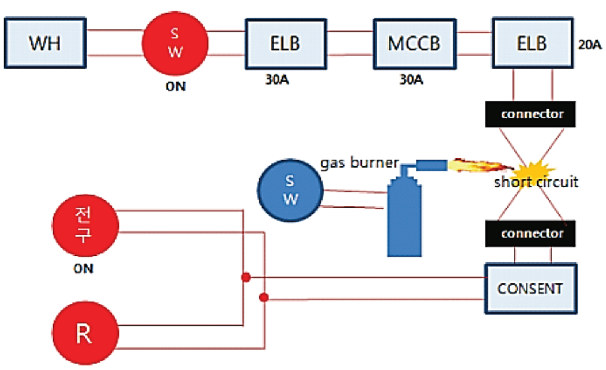


Figure 5 Secondary dragon mark generation equipment

3.2 Generation of Raw Data by Secondary Dragon Marks

Fig. 5 shows the situation in which commercial power (220 V, 60 Hz) is applied and the load (light bulb and electrical equipment) is connected as the second method of melting traces. The gas burner is operated between the electrical short connectors to artificially melt the + and – wires with a flame to generate an electrical short circuit (SHORT CIRCUIT), and then use the molten wire as raw data [16].

3.2.1 Data Acquisition by Secondary Dragon Marks

Fig. 6 shows the selection of secondary traces that are short-circuited due to burning of the wire sheath due to the heat of the fire.

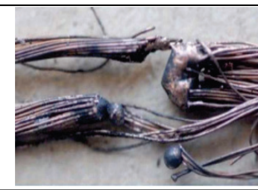
2nd dragon mark	
1 line	stranded wire
	

Figure 6 2nd dragon mark

3.3 Generate Fifteen Raw Data

The heatstain generation method is a method to check the cause of the fire when the commercial power (220 V, 60 Hz) and the load (light bulb and electrical equipment) are cut off. The gas burner is operated between the electrical short-circuit connectors regardless of the fire as traces of metal such as wires being melted by the heat of fire. After artificially melting the + and – wires with flames, the molten wires are used as raw data [17, 18]. Fig. 7 shows the selection of the heat traces from the molten wire due to the heat of fire in a state in which electricity is not energized.

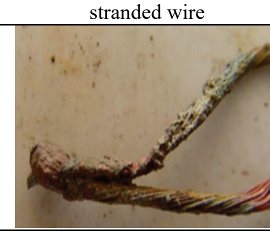
forty	
1 line	stranded wire
	

Figure 7 Forty

3.4 Utilize Data for Artificial Intelligence Learning

3.4.1 Use of Electric Fire State Judgment Data Set

It is a service cooperation that utilizes data such as external companies, institutions, and individuals built to support the construction of platforms and portal sites. It supports technology by discovering services in AI technology based on electric fire status judgment data and utilizing user community. Here, for the feedback and update of the electric fire state judgment dataset published through the AI hub, the required service item extraction and interface are provided through the modular implementation of the Open API. UI/UX implementation according to usability through individual provision it implements UI/UX according to usability through the extraction of necessary service items and individual provision of interfaces through modular implementation of Open API. Fig. 8 shows the linkage with various DBs through modularization of domestic and overseas DBMS linkage adapters.

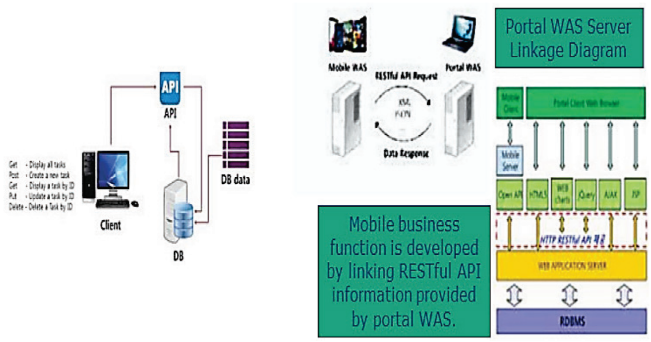


Figure 8 Open API system structure diagram and API portal utilization solution WAS connection processing diagram

3.4.2 Spread of Data for AI Learning

In building a data value chain ecosystem, a value chain ecosystem is established by discovering new values through public-private data connection and openness for the combination/analysis of various heterogeneous data. Data-related technology development and decision-making tool R&D support, data and artificial intelligence infrastructure reinforcement, AI manpower expansion, and cooperative ecosystem are established. Create a data business and establish a data-centered virtuous cycle system by strengthening data access/analysis/utilization by preparing legal data distribution methods. In order to support the infrastructure to utilize data from all industrial fields linked to the AI cluster, data from the national/social/industrial fields are integrated and managed by the AI cluster. Data utilization infrastructure support measures such as space and computing resources for public-private data linkage are also needed. In addition, it is necessary to support the improvement of data utilization capabilities by securing know-how for data utilization and profit creation through active cooperation with overseas advanced companies, and accumulating experience in conducting business. To secure IoT sensor data, which is a prerequisite for securing source data, organizations related to the Internet of Things (IoT) industry and corporate cooperatives are formed. In order to increase the utilization of AI Hub, it is necessary to prepare a plan to provide data provider rewards through simplification of the sign-up process, introduction of My Data, and alliances between various companies such as credit card companies. Companies share AI learning datasets by industry group in consideration of the purpose of using data for AI learning. As a shared hub that can spread datasets, a cloud-based learning data sharing center for each industry group is installed to increase the utilization of AI Hub. In order to strengthen data connectivity for AI learning between companies, starting with the standardization of API standard protocols for platform linkage in a global-oriented open ecosystem, a data set linkage system for artificial intelligence learning is configured. Establish an integrated platform and platform operating organization for data set interworking so that real-time sharing, update, and feedback of data sets for artificial intelligence learning can occur.

4 DEVELOPMENT OF AI DATA UTILIZATION MODEL

4.1 Electric Fire Status Judgment Data

Data utilization model development for AI learning is a representative dataset CIFAR-10 of SOTA (State of the art) Image classification part. This is a search for model candidates that are open as open source among models with high performance and are customizable and used universally. DenseNet re-uses features by connecting the feature maps of all layers, significantly lowers computational complexity by reducing the number of parameters, and applies SOTA performance to a small number of parameters.

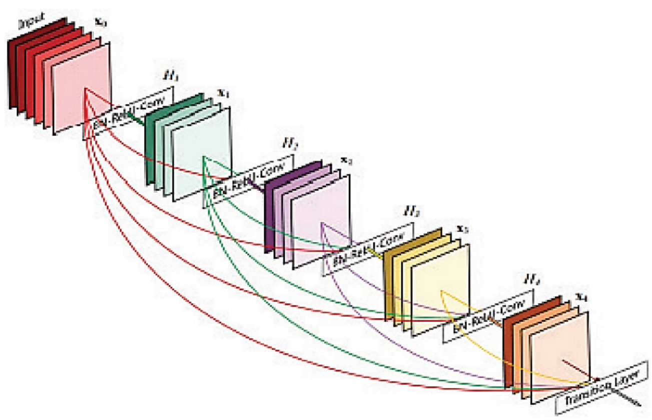


Figure 9 5-layer dense block

In Fig. 9, DenseNet consists of 3 Dense Blocks and 2 transition layers. Unlike ResNet, which combines previous information, it is a structure that preserves information by concatenating multiple networks. As a learning method, DenseNet connects all layers to ensure that the flow of information is maximized. Therefore, the input image is passed through the convolution layer to extract features, and then the feature information is connected without merging and transmitted to the next layer.

Layers	Output Size	DenseNet-121($k = 32$)	DenseNet-169($k = 32$)	DenseNet-201($k = 32$)	DenseNet-161($k = 48$)
Convolution	112 × 112	7 × 7 conv, stride 2			
Pooling	56 × 56	3 × 3 max pool, stride 2			
Dense Block (1)	56 × 56	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6	[1 × 1 conv, 3 × 3 conv] × 6
Transition Layer (1)	56 × 56	1 × 1 conv			
	28 × 28	2 × 2 average pool, stride 2			
Dense Block (2)	28 × 28	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12	[1 × 1 conv, 3 × 3 conv] × 12
Transition Layer (2)	28 × 28	1 × 1 conv			
	14 × 14	2 × 2 average pool, stride 2			
Dense Block (3)	14 × 14	[1 × 1 conv, 3 × 3 conv] × 24	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 48	[1 × 1 conv, 3 × 3 conv] × 36
Transition Layer (3)	14 × 14	1 × 1 conv			
	7 × 7	2 × 2 average pool, stride 2			
Dense Block (4)	7 × 7	[1 × 1 conv, 3 × 3 conv] × 16	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 32	[1 × 1 conv, 3 × 3 conv] × 24
Classification Layer	1 × 1	7 × 7 global average pool			
		1000D fully-connected, softmax			

Figure 10 DenseNet architectures for ImageNet

The Pooling Layer in Fig. 10 is used for downsampling between dense blocks, and when the output comes out to the last dense block through the transition layer that changes the

1×1 conv layer to 2×2 avgPooling, it passes through the classification layer and outputs the result.

As a learning method, DenseNet connects all layers to ensure that the flow of information is maximized. Therefore, the input image is passed through the convolution layer to extract features, and then the feature information is connected without merging and delivered to the next layer.

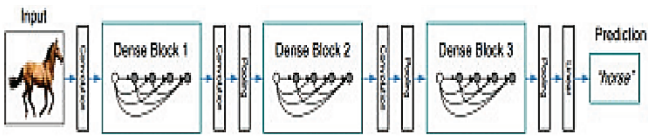


Figure 11 3-dense blocks DenseNet Learning method

In Fig. 11, through the connection, each layer can directly access the loss function and the gradient from the input signal, making it easier to learn features.

4.2 Selection of Learning Model Quality Indicators

In the learning method, the graph in Fig. 12 below shows FLOPS (FLoating point Operation Per Second) when width, depth, and resolution are increased, respectively. Width, depth, and resolution all quickly saturate up to 80 % Accuracy, and performance improvement after that is imited. To combine width, depth, and resolution, the depth is set to α, width β, and resolution γ, and α, β, and γ that satisfy $\alpha \times \beta^2 \times \gamma^2 \approx 2$ when $\varphi = 1$ are searched through grid search. Find out. (The values of B_o are $\alpha = 1.2$, $\beta = 1.1$, $\gamma = 1.15$) Here, if α, β, and γ are found through grid search, φ(0, 0.5, 1, 2, 3, 4, 5, 6) is used to make the final result. To create a factor to multiply the existing width, depth, and resolution and use it.

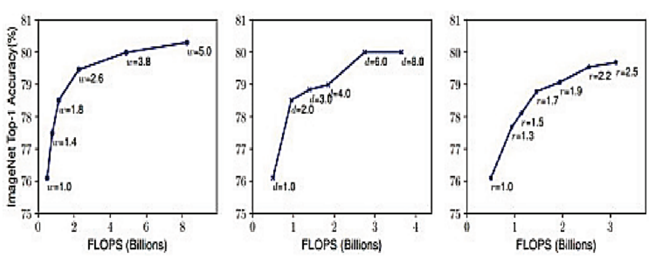


Figure 12 ImageNet Top-1 Accuracy of FLOPS according to w, d, r

Table 1 Class model indicator

		Predicted Condition	
		Positive(PP)	Negative (PN)
Actual Condition	Positive (P)	True Positive (TP)	False Negative (FN)
	Negative (N)	False Positive (FP)	True Negative (TN)

The accuracy of a machine learning classification algorithm is a measure of how often the algorithm correctly classifies data points. Accuracy is the number of correctly predicted data points among all data points. Building a fire detection and electric fire judgment data set can contribute to job creation by using cloud sourcing for AI learning data collection, processing, and verification. In the future, accuracy will be used together with other quality indicators such as precision and recall using various ratios of true/false, positive/negative, as in Tab. 1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

5 CONCLUSION

In this study, when the insulation of the wire is destroyed, a closed circuit of the power supply is formed without the load connected, which is called a short circuit. In the event of a short circuit, there is no load, so the resistance becomes zero, so according to Ohm's law, the current becomes infinite, which becomes very dangerous.

As a result of these studies, it is possible to efficiently respond to disaster situations by monitoring the fire scene in real time through on-site photos of electrical fires caused by electrical causes. In addition, accuracy can be achieved by identifying the exact cause of the fire. In addition, objective supervision that excludes the subjectivity of fire detectors can maximize the reliability and accuracy of inspection results. Technology using the electrical fire judgment data set is used in the actual field, which can reduce the cost of fire scene inspection, such as rapid cause identification and manpower problem resolution. In addition, it can contribute to the development of other disaster safety design systems, which is expected to greatly increase market competitiveness.

In the future research, the developed platform will combine electrical fire judgment data and various datasets in fire detection, and link it with big data AI algorithms to realize technology such as situation recognition and judgment technology as a state-of-the-art system. By advancing smart identification technology, avatars are used to collect professional data related to electrical fires, expanding the scope of application in other similar facility monitoring system fields, greatly contributing to the life safety of the people.

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