Review on integration of ontology and deep learning in cultural heritage image retrieval

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Article Info ABSTRACT

ontologies with cultural heritage domains.

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Image retrieval methods are currently developing towards big data processing. The literature review is focused on image big data extraction with cultural heritage domain as training and testing datasets. The development of image retrieval process starts from content-based using machine algorithms, deep learning to ontology-based. Image recognition research with cultural heritage domain is conducted because of the importance of preserving and appreciating cultural heritage, in this case, cultural heritage images such as Indonesian Batik are discussed. Batik motif images are Indonesian cultural heritage that has thousands of motifs that are grouped into many classes with a non-linear hyperplane. The problem is focused on processing big data that has many classes. Currently research is evolving into knowledge-based image retrieval using ontologies due to semantic gap constraints. The results of this literature study can be the basis for developing research on the application of appropriate deep learning algorithms so as to utilize the hierarchy of classes and subclasses of image

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1. INTRODUCTION

Image information in the cultural heritage domain needs to be known and understood by the people who own it, so that the current generation can protect and learn the noble values, local wisdom, customs and culture of their predecessors in the past. Emerging research in the field of image retrieval can help document knowledge in identifying, categorising, and preserving images in the cultural heritage domain.

Research in the field of image retrieval is still being conducted today, due to the influence of the interconnected domains of the web, big data, ontology, and deep learning. What is done in Image Retrieval is the calculation of similarity in images, in content base image retrieval (CBIR) the search for similar images based on colour characteristics, image edges, texture, or based on spatial information [1]–[3]. The application of CBIR on web documents is increasingly inadequate because it has problems with big data. Big data documents occur due to information that is continuously uploaded to the internet, so that documents have a very large volume of data with many classes, heterogeneous, and very fast growth in number, and have unstructured and semi-structured data forms [4]–[8]. Previous CBIR research with an image dataset in the cultural heritage domain had a high accuracy of 96.7% when applied to classification with two classes [9], in subsequent research with the same data and methods applied to multi-class classification decreased accuracy [3], [10], the same multi-class classification method tested with large data decreased accuracy and training time became very long [3]. In handling very large data waves and many classes, CBIR has developed from

machine learning that applies shallow learning to the use of deep learning [5]–[7], [11]. Deep learning does not require separate feature engineering as in shallow learning, so that it can automatically extract features and is faster and can identify complex feature patterns and many similarities between images in very large data. Deep learning is a continuation of machine learning in image retrieval classification on big data with a large number of classes [12]. The application of image retrieval on the web with deep learning still has shortcomings, because deep learning only focuses on feature representation without considering the relationship of concepts in the image [12], [13].

The web has a very large amount of data, to be able to understand/make decisions about the data it has, a semantic web is needed [14]. The core of semantic web technology is applying ontology to represent information into a knowledge base that can be understood and processed by machines [14]–[17]. Ontology can organise concepts and relationships between concepts in a knowledge domain, and provide an explanation of the important properties of each concept through attribute values [17]–[19]. Ontology can change the view of document orientation towards interrelated knowledge, and can be used in knowledge management systems. Ontologies contain interrelated knowledge with a structured and semantic-based representation [14], [20]. Ontology-based data models are used to store a knowledge database. In image retrieval, ontologies are used to form a conceptual model of recognised objects, such as their physical characteristics and relationships with other objects. Thus, determining the identification of the image domain that is the object of search is important in building the right ontology, because it will get an image dataset that is relevant to the domain [17].

Ontology, on the other hand, is one of the key concepts and main media in the research field of Semantic Web, because it can be a good basis for building semantic functions [18], [21]–[23]. Ontology is needed to solve the semantic gap problem, which is the gap between visual meaning low level feature and textual meaning high level feature [21], [24]. Ontology with spatial information of objects in the image can facilitate CBIR in improving image retrieval, by retrieving images on the semantic web. Ontology is needed to solve the semantic gap problem, which is the gap between visual meaning low level feature and textual meaning high level feature [21]. Ontology with spatial information of objects in the image can facilitate CBIR in improving image retrieval, by retrieving information of objects in the image can facilitate CBIR in improving image retrieval, with spatial information of objects in the image can facilitate CBIR in improving image retrieval, with spatial information of objects in the image can facilitate CBIR in improving image retrieval, with image retrieval on the semantic web. Although previous research has explored ontology methods in CBIR, there is no universal approach to a standardised methodology for building ontologies [18], [19]. In general, the object of ontology development research is the development of a domain knowledge ontology framework with user-view ontology, which consists of developing user-view mapping with command ontology, and mapping command ontology with local schema ontology of data sources.

The successful application of ontology can improve the efficiency and user friendly performance of image retrieval on the semantic web by building a search mechanism that can minimise getting irrelevant image information (high precision) and can ensure that relevant image information is not missed (high recall). The calculation of similarity, precision and recall values can be used to see the success of the introduction of content-based image retrieval with ontology. The results of image retrieval can be improved by storing indexing images on semantics by creating a meaning based index structure using a concept based model with domain dependent ontology [16]. In this research, the development of a spatial ontology model with topological relations that supports the analysis of texture patterns through spatial information with a statistical parameter feature content approach.

In an effort to resolve the gap in understanding the key meaning, ontology design is carried out to store information and become a good basis for building semantic functions, so that ontologies can facilitate machines to process and understand information so as to improve services for users. Ontologies can help identify relevant feature patterns in images, and can improve semantic understanding of image content [25]. For example, image retrieval research in recognising cultural heritage image domain, in this case Indonesian batik image [3], [9], [10]. Batik is an artwork of drawing motifs on fabric media, which is coloured by a waxresist dyeing process, and uses tools called "canting" and "cap" [26]. CBIR research on classification to recognise Batik motifs with many datasets and classes has problems with the training speed and classification process [3], so in this case the concept of ontology is needed. Ontology can create a concept hierarchy by identifying role relationships between concepts related to batik image characteristics such as types of batik motifs, commonly used colours, fabric types, regions of origin, and other characteristics contained in batik images, so that users can search based on the categories specified in the ontology [27]–[29].

With the extraordinary diversity of Indonesian Batik motifs, and having been officially recognised by UNESCO on 2 October 2009 in the list of the heritage of humanity for oral and intangible culture. To further introduce the diversity of Indonesian Batik motifs to the international arena, it is necessary to provide a knowledge base as a centre of information on Indonesian Batik, specifically one that can be freely accessed via the internet. The existence of this service can be said to be important so that the diversity of Indonesian Batik works can always be known by many parties, especially the Indonesian people. The development of Batik Indonesia information availability services can be seen not only in the form of a web-based application that processes more data into information aimed at users. In addition to users, the information availability service must also be able to support the exchange and linkage of data between one information object and other information objects. For example, information on an object of Indonesian Batik certainly has a connection to information services on cultural objects of Indonesian art performances. To be able to support these needs, it is necessary to implement an approach that supports the openness of data services. One of the application frameworks that can support this is the Semantic Web standard [27], [30].

By integrating ontology and deep learning together, Indonesian Batik image retrieval is expected to be more accurate, faster, and more efficient. The deep learning model is trained to recognise Batik image motifs based on the concepts contained in the ontology [27], [28]. In deep learning, ontology is used to describe and organise the meta data of batik image as a cultural heritage image, by creating a conceptual structure to organise the information contained in Batik image motifs by grouping them into classes, by building a deep learning model that is more efficient in learning and recognising image features. The model is trained using image datasets that have been annotated with ontology information. Ontology and deep learning can be used together in image retrieval systems, ontology is used to map concepts, and relationships between concepts in images, while deep learning is used to learn features and patterns from image data and predict image labels. By combining the concepts of ontology and deep learning, it can improve the performance of the image retrieval system to interpret images better by achieving higher accuracy, and better efficiency in recognising objects or entities in Batik image motifs as images in the cultural heritage domain.

In handling very large data waves, CBIR is evolving from machine learning that applies shallow learning to the use of deep learning. Deep learning does not require separate feature engineering as in shallow learning, so as to improve performance and speed in recognising images on very large data [31]. Research on the relationship between ontology and deep learning in recognising images as a cultural heritage domain is still developing, and analysis of various approaches and techniques is still needed. CBIR research on big data batik images with geometric motifs [3], [10], is currently still limited to deep learning research in the feature extraction or classification part to produce maximum image recognition accuracy. In general, an important problem in image retrieval is how to build a comprehensive, relevant, and precise ontology design with a deep understanding of the domain under study to support image retrieval. The next problem is how to utilise the ontology to generate better simantic annotations for training deep learning models to improve image retrieval performance. An important aspect of deep learning is the optimal extraction of features from images, so the challenge is to design ontologies that can provide classifications based on relevant and informative features for use in deep learning models. Features can correspond to a single attribute or a composite representation of multiple attributes.

2. METHOD

This literature review discusses the development of image retrieval research in the domain of cultural heritage image datasets. The discussion of the literature review specifically on content-based classification methods ranging from the application of machine learning algorithms, deep learning to ontology-based. The discussion phase carried out is with the stages:

- i. Identification of research topic area: discussing the importance of content-based image retrieval for images with cultural heritage domain, in this case with Indonesian Batik image as the knowledge base.
- ii. Applying appropriate keywords in this review to better focus the discussion on identifying methods applied in previous studies.
- iii. Search for relevant literature sources with keywords to understand and synthesize the problems of methods used in previous to current research. In general, the development of classification starts for small to large datasets, with the application of machine learning. Then it develops for big data datasets with the application of deep learning, and ontology.
- iv. Future research potential, in the form of a conceptual framework as a basis for developing deep learning and ontology linkages with the cultural heritage image domain.

3. RESULT AND DISCUSSION

In this section, there is a comprehensive discussion of the methods that have been applied in previous research to date, and a conceptual framework for future research. The results of this literature review are presented in two subsections.

3.1. Review of content-based image retrival

One of the researches in the field of digital images is for content-based image recognition. The image recognition classification process uses image content information obtained from training and testing

datasets, the dataset is the result of feature extraction from several image attributes which are the implementation of meta data related to the content of shape, colour, texture, or other details that can be obtained in the image itself [2], [4], [32]–[34]. Unlike the text base that uses features in the form of meta data containing tags, keywords, or descriptions annotated with images. Image search on the web that has a very large database, the use of text-based meta data still produces many results that are not appropriate.

Content-based image recognition uses a feature extraction algorithm, which is processing to obtain image characteristics in the form of low-level features [9], [32]–[34]. This process examines each pixel to obtain a feature vector for each image. Each image is extracted to produce feature values in the feature vector that are unique characteristics of the image, so that it can be distinguished from other images. It is necessary to analyse the application of the best algorithm for finding the feature vector that best suits the classification algorithm to be applied. CBIR research is also developing in the application of hybrid algorithms, such as in improving classification results by applying hybrid fuzzy system, decision tree (ID3), and assosition function algorithms [35].

In obtaining feature values, statistical and spectral methods can be used. In statistical methods, statistical calculations are used for the grey level distribution by measuring the degree of contrast, granularity, and roughness in the neighbourhood between pixels as a function of orientation and spatial distance in the digital image. Spectral methods are transformation methods such as Fourier and Wavelet. Fourier transformation is to obtain clearer feature extraction information by converting the spatial image domain into the frequency domain. Wavelet transformation improves the Fourier transformation which only determines the frequency that appears in a signal but cannot show the time when the frequency appears. Wavelet transformation of the time when the frequency appears [9].

Image retrieval research applied to Indonesian batik motifs is carried out to protect Indonesian batik motifs as cultural heritage and introduce more knowledge of batik motifs to the world community. In previous research, both statistical and spectral methods were developed for use in CBIR [36]. Finding batik image recognition in CBIR requires a feature extraction method that is appropriate for use in generating feature datasets. Feature extraction is a fundamental part of classification, because the feature dataset resulting from good feature extraction can maximise the accuracy of the classification results. Various feature extraction methods that can be used are histogram, co-ocurrence matrix, gradient, edge detection, fractal, Fourier spectrum, and wavelet. The feature dataset resulting from feature extraction is used to recognise the image with classification algorithms. Classification algorithms can use hierarchy-based decision tree, knearest neighbourhood algorithm, k-means and minimum-distance based partitioning, and artificial neural network (ANN) based such as perceptron algorithm, backpropagation neural network (BNN), and suppot vector machine (SVM). Each image is extracted to produce feature values that are unique characteristics of the image, so that it can be distinguished from other images. Features are unique characteristics of the texture characteristics of the image so that it can be recognised through digital image processing. To measure texture characteristics, the feature extraction analysis method is fundamental to image analysis [37]. The first step in classification is to perform feature extraction. The results of feature extraction are represented as statistical characteristics that are used for classification in the recognition phase.

Structural methods perform feature extraction by forming a definition of micro-texture components based on the spatial arrangement rules of the micro-components. The features obtained from structural methods are more useful for the synthesis process than for image analysis. For image analysis, statistical and spectral methods can be used. In statistical methods, statistical calculations are used for the grey level distribution by measuring the degree of contrast, granularity, and roughness in the neighbourhood between pixels as a function of orientation and spatial distance in the digital image. Spectral methods are feature extraction using transformation methods such as fourier and wavelet. Fourier transformation is to obtain clearer feature extraction information by converting the spatial image domain into the frequency domain. Wavelet transformation improves the Fourier transformation which only determines the frequency that appears in a signal but cannot show the time when the frequency appears. Wavelet transformation can show the scale or duration of the time when the frequency appears. From the wavelet transformation a unique value is produced that characterises each batik image, the value consists of the energy value and the standard deviation standard value calculated from the subband wavelet coefficient at each level of transformation [9], [38]. In getting the feature value, the right method is needed to produce the best feature value, where the best feature value can maximise the accuracy of the classification results. The dimensions generated at the feature extraction stage are sometimes still too high, as well as the presence of irrelevant and redundant attributes that can reduce performance at the classification stage [39], [40]. Feature dimension reduction can be done by selecting the best features so that performance at the classification stage can be improved. Feature selection can be done by feature reduction by selecting features that have the best variance.

In the recognition phase, image classification is performed based on statistical feature parameters from the feature extraction results. Classification aims to categorise the class of an object based on the

training feature dataset. Classification can be defined as the process of training a target function f that maps each feature set x to one of a number of class y levels. The resulting target function training model f is used to recognise the class of the test feature set. Statistics, decision trees, and artificial neural networks are the methods used in the research to evaluate image recognition based on motif texture characteristics. Artificial neural networks (ANNs) are a combination of statistical and tree-like learning methods but have higher complexity, they mimic human thinking not only in a clausial (if-then) manner, but can be more flexible in solving problems that cannot be solved by linear methods.

The application of CBIR with shallow learning that uses feature extraction and classification algorithms separately is a machine learning technique in image recognition. Machine learning techniques evolved into deep learning techniques that apply neural networks with many layers. Deep learning is more used for image recognition needs with very large data with complex features based on semantic content or complex visual images. Such huge data with rapid growth is known as big data [13], [41], [42]. Deep learning does not require separate feature engineering, the feature extraction algorithm and classification algorithm become one in a deep learning model, for example as in the convolutional neural networks (CNN), recurrent neural networks (RNN), AlexNet, zfNet, Google Net, and ResidualNet algorithms.

Batik has various patterns and complex designs. By utilising deep learning in CBIR with a large dataset of batik images, it will be able to classify batik patterns with high accuracy. The deep learning architecture allows the model to automatically extract a hierarchy of features from the image and classify [41], [42]. One of the important reasons why the application of deep learning is needed, because in the application of shallow learning for batik image classification experiments with increasingly large datasets and many non-linear classes will require an increasingly large training time [3], [43], [44], which can make it impractical for application development where computing time is one of the critical factors.

3.2. Development of ontology-based batik image retrieval research

Research in the field of image retrieval continues to grow in the domain of web, big data, ontology, and deep learning. Research in the field of image information on the web has a problem where it has a very large amount of data and the increase in the amount is very fast, or known as big data. This development leads to ontology based image retrieval (OBIR) research that can help overcome the problem of image recognition with a very large number of classes with a high variation in texture similarity [15], [25]. Classification results with deep learning using CNN [45] and region-based-CNN [46] algorithms can improve the efficiency of image retrieval based on the ontology built. The improvement is due to the assignment of low-level features into high-level semantic based on the ontology of image knowledge.

Previous ontology-based image retrieval studies with datasets in the domain of cultural heritage images generally exploit ontology models for semantic enrichment of cultural heritage images [47]–[49]. In the initial phase, a domain-specific understanding is required, so that the simantic representation can be deeper, and relevant information can be searched and retrieved according to user needs [50], [51]. The development of batik image recognition ontology is a very complex research and requires in-depth knowledge of the batik domain as a cultural heritage. Batik is a traditional textile artwork that is a distinctive culture of Indonesia and is a hereditary tradition [52]. Indonesian batik is a process of fine art and colouring on cloth with wax-resist dyeing techniques, and produces motif images in the form of patterns or patterns that have meanings related to the culture of the place where the batik is made [26], [53], [54]. There are thousands of batik motifs spread across Indonesia, so a batik knowledge library is needed by integrating ontology and deep learning models used in motif identification in batik images, or semantic-based search.

CBIR utilising deep learning is an effective technique for image recognition today, but the problem is that deep learning techniques only focus on feature representation without considering the relationship between the concepts underlying the image. Content-based image retrieval is still limited to recognising image features based on colour, texture, and shape in statistical values called low-level features, which still has a semantic gap to human conceptualisation in defining image feature recognition [16], [17], [21]. By utilising ontologies, it is possible to bridge the semantic gap, thus improving the accuracy of image recognition by taking into account the relationships between concepts in the ontology. Ontologies formalise the definition of image features in terms of words through concepts represented as classes, sub-classes, and individual variables, such representations can use ontology web language (OWL) [48], [55], [56]. The progress of the use of OWL is also supported by research in the field of improving web service technology and service oriented computing, especially in the field of web service description language [57]. Ontologies should include all classes and sub-classes that are relevant and consistent with Indonesian batik image knowledge. The ontology can generate simantic annotations for deep learning training to produce optimal, relevant and informative features. The integration between ontology and deep learning model is used in motif identification in batik images, or semantic-based search.

In image recognition, the number of classes or objects to be identified can be very large, and ontologies can help organise and classify these classes. The essence of semantic web technology is to apply

ontologies for the representation of information into a form of knowledge base that can be understood and processed by machines [16]. The research of ontology linkage with deep learning for image recognition is very important to improve the accuracy, efficiency, scalability, interpretability, and applications of image recognition systems in various fields. In the long run, this research can bring great benefits to technology development and daily life. By utilising ontologies, the accuracy of image recognition can be improved by taking into account the relationships between concepts in the ontology which can help identify groups of objects with a large number of classes [15], [16], [21].

Content-based batik motif recognition on the semantic web with a huge amount of image storage with different field names will occur simantic gaps, so there is retrieval of irrelevant images and missed information from relevant images [16], [27]–[29], [36]. To minimise the semantic gap in the search mechanism, a knowledge base is needed to understand the content, namely by creating an ontology domain using interrelated knowledge topology relations in implementing content-based batik motif recognition. The weakness of using text-based metadata in recognising images is that there are difficulties in describing in words, and to get the correct query, the user must know the complete knowledge domain [16]. To overcome these problems, content-based can be utilised by utilising image processing technology, namely by searching for batik motifs based on texture similarity and spatial information that has knowledge of the meaning and regional origin of the batik motif. What is discussed in the development of current research is how to develop a segmentation and feature extraction model that can be used appropriately to produce queries by batik image content containing low-level feature datasets that contain texture, shape, and colour characteristics as distinguishing characteristics of batik motif patterns. As well as how to develop domain knowledge in the form of a high level ontology concept model by flattening low level image features to improve the results of the matching classification in batik image recognition from existing datasets.

Ontologies generate relevant and informative features, and being integrated into a deep learning architecture can improve the interpretability of the model, and ensure that the model can understand the context of the analysed image. In understanding the context of batik images, ontologies perform semantic representation in the domain of batik image concepts [27]–[29]. In the initial stage, it is necessary to identify key concepts relevant to the batik image, and describe the concept hierarchy and semantic relationships between them to create a batik ontology [27], [56], [58]. Define classes, subclasses, properties of each class, and individual variables properly to give clearer meaning to entities and their relationships in the context of batik image. The research methods developed to improve batik image retrieval are as:

In the initial stage, the Indonesian batik image is determined as the domain (main class) and the scope of the ontology. In this image retrieval ontology has the scope to recognise the diversity of traditional batik images from Indonesia as a rich cultural heritage that has meaning for each motif. The proposal as the basis for developing a conceptual ontology to recognise Indonesian batik motifs is as:

- Domain: Indonesian traditional Batik: Define as the main class that represents the main entity in this ontology, which is a work of art painted on fabric as an original Indonesian cultural heritage.
- Class: Consists of two user view terminologies based on the motif produced (example of motif as shown in Figure 1): (i) "Keraton" (palace) Batik class (example of motif as shown in Figure 1(a) to (d)) and (ii) "pesisir" (coastal) Batik class (example of motif as shown in Figure 1(e)).

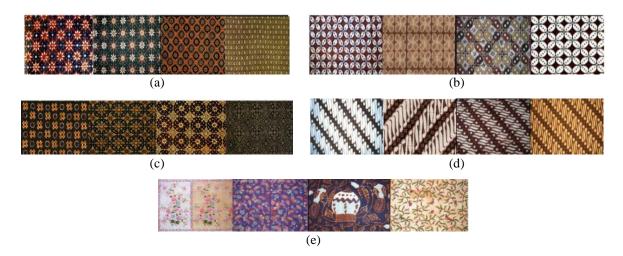


Figure 1. Examples of "keraton" batik motifs and "pesisir" motifs: (a) ceplok, (b) kawung, (c) nitik, (d) parang, and (e) pesisir

Ontology properties: These properties are based on the user view, where they are always present in every class as: (i) City origin property: A property that links the batik-producing city origin instance with the batik class instance. The origin city of the palace batik class (Solo and Yogyakarta), and 16 coastal batik class producing city origins (Gresik, Lasem, Tuban, Madura, Banyumas, Rembang, Demak, Kudus, Pekalongan, Tegal, Inderamayu, and Cirebon. Then it developed to the West Java region in the Garut, Tasik Malaya, Ciamis areas, and developed to Betawi batik); (ii) Properties of motif elements: A property that connects the motif element instances contained in the batik image with the property instances of the origin city and batik class. In traditional Indonesian batik art, there are motifs that consist of a combination of several traditional batik patterns. There are many palace batik motifs such as: Parang, kawung, ceplok, nitik, cement, sidomukti, truntum, sawat, slobog, bondet, pamiluto, and so on. Motifs for coastal batik are influenced by the origin of the city, such as motifs: flora and fauna, flowers, nature/clouds, roosters, leaves, stars, and puppets; (iii) Philosophical properties: A property that connects the philosophical instances or moral messages contained in each batik motif with the property instances of batik motif elements and classes; and (iv) Batik type property: Properties that connect batik type instances with batik class instances, based on the manufacturing technique and tools (tools for making batik shown in Figure 2), namely: "tulis" (writing) technique with "canting" tools (Figure 2(a)), and "cap" (stamp) technique with "cap" tools (Figure 2(b)).



Figure 2. Tools for making batik: (a) "canting" and (b) "cap"

- Individual variable: Batik X: An individual variable that represents an instance of batik. This variable will be associated with instances of the class Batik pesisir or Batik keraton. There are thousands of batik names based on motif, philosophy, type, and city of origin.

The results of the ontology definition are then defined into the local schema data source, by creating a file format or local data structure to store batik image information. The next stage is to develop mapping local schema data source with commod ontology, to implement the mapping between classes, properties, and relationships in the ontology with the data structure in the local schema data source. Defining the conceptual ontology is expected to improve classification results with more detailed image annotations [23], [59], [60]. The annotated images from the conceptual ontology become inputs in the hypernym and hyponym classification stages which can reduce or minimize the number of training datasets so that the time for the training process is faster [23], [59]. The initial classification hypernym is a general classification consisting of only two classes of palace batik and coastal batik, the next classification hypernym of palace batik consists of 2 classes and coastal batik consists of 16 classes based on the origin of the city, the hypername continues to follow the ontology developed based on motifs, types, and philosophies. The final result is a special classification result from hyponym classification in the form of an image as an individual variable and its annotation.

The next stage of the research work is how to improve the accuracy of image retrieval by training a suitable deep learning model using ontologically annotated image data. Deep learning algorithms are good for applying to big data with Indonesian batik datasets that have many classes with non-linear hyperplane, this is because deep learning algorithms can speed up the classification process, because the process does not require a separate feature extraction stage with a separate feature extraction algorithm [23]. The ontology results in a hierarchical structure that has defined the relationship between batik image knowledge concepts. The process at this stage requires experimentation to adjust the parameter values of the deep learning model to understand the relevant patterns and features in the batik image dataset that has been annotated using

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ontology. By linking ontology information into the learning process and pattern recognition with deep learning models, experiments are needed to apply the right deep learning algorithm to design a deep learning algorithm model structure that utilizes the ontology hierarchy. In the final stage, the deep learning algorithm used is evaluated, not only based on the performance of the increase in the accuracy value of the classification results and the time of recognizing the Batik motif image, but also testing the extent to which the applied algorithm can understand the ontology structure and semantic relationships in it.

4. CONCLUSION

This discussion is the basis of a strong foundation in the development of systems to understand semantic content, and applied to documentation in conveying information about cultural heritage more effectively. The integration of ontology and deep learning in Batik image retrieval research in the context of preserving and managing cultural heritage documentation is expected to improve the model's understanding of the semantic content of images, resulting in more relevant and contextual search results. The research stages of integrating ontology and deep learning to improve cultural heritage domain image retrieval performance require research, development, and a deep understanding of both ontology and deep learning that can help achieve better integration. Integrating ontology into deep learning can process the images and understand the semantic content better, thus improving the system's ability to recognise and describe the information contained in cultural heritage domain images.

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