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An Ontology-Based Contextual Knowledge Representation for Semantic Image Segmentation

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Abstract**—** Contextual Hierarchical Model (CHM) was a semantic image segmentation model which learned contextual information in a hierarchical framework. A Logistic Disjunctive Normal Networks (LDNN) classifier was used in each hierarchy level of CHM for semantic image segmentation. The class average accuracy of CHM may be affected due to the absence of global constraint. So, different Conditional Random Field (CRF) models were introduced to define global constraints through energy functions on a discrete random field. The efficiency of CHM based semantic image segmentation was greatly depended on the performance of LDNN. The performance of LDNN was enhanced by using a proximal gradient which minimizes the quadratic error of LDNN with fast convergence rate. Moreover, a Grey Wolf Optimization (GWO) algorithm was introduced to optimize the user specified weight and bias terms of LDNN which reduce the time complexity of LDNN. In this paper, CHM based semantic image segmentation is further improved by using ontology-based contextual knowledge representation in CHM. The ontology-based contextual knowledge representation constructs a relation based on taxonomic relations. In order to tackle the complex types of relations in images, a fuzzification is introduced in the ontology which is used to define the semantic relation between the concepts more effectively. Based on the fuzzified taxonomic relation, a relation is constructed which is given as additional input to the CHM for semantic image segmentation. The ontological taxonomic knowledge representation adjusts the segmentation results of CHM based on taxonomic relations. The experimental results show that the proposed Ontology-based contextual knowledge representation with CHM- Higher order Hierarchical CRF-Improved Optimized LDNN (OCHM-HHCRF-IOLDNN) has better performance in terms of class accuracy, pixel accuracy, F-measure and G-mean than the other method.

Keywords**—** Semantic image segmentation, Contextual Hierarchical Model, Logistic Disjunctive Normal Networks, ontology-based contextual knowledge representation, fuzzification.

I. INTRODUCTION

Semantic image segmentation [1,2] is a fundamental step in image processing [3,4]. The main intention of the semantic image segmentation process is to segment the image accurately and annotate each segment with its true semantic class. The semantic image segmentation is considered as a primary step towards image understanding and it integrates detection and segmentation in a single framework. The semantic image segmentation has to consider the short-range and long-range contextual information for efficient labeling of pixels. Various approaches [5,6] have been used to obtain contextual information for semantic image segmentation. But these approaches cannot obtain the contextual information at multiple scales.

A Contextual Hierarchical Model (CHM) [7] was proposed for semantic image segmentation which obtains contextual information at multiple resolutions. The CHM model learned a series of Logistic Disjunctive Normal Network (LDNN) classifiers consecutively at multiple resolutions. Because of the absence of global constraint in CHM, the class average accuracy was affected. So, a global constraint was defined through different Conditional Random Field (CRF) models [8] which improved the class average accuracy of CHM. The LDNN [9] classifier was improved by using a proximal gradient method and the weight and bias term of LDNN were optimized by Grey Wolf Optimization (GWO) algorithm [10,11]. It effectively exploited the contextual information for semantic image segmentation.

The main contribution of this paper is listed as follows:

1. CHM-IOLDNN based semantic image segmentation is further improved by using the contextual information along with the ontological taxonomic knowledge representation.
2. The usage of ontological knowledge representation adjusts the segmentation and labeling results by means

of fine-tuning the membership degrees of detected concepts in the ontology.
3. The semantic image segmentation accuracy is improved by using the ontological taxonomic knowledge representation which defines a large number of distinct and diverse relations among objects in images.

The structure of this paper is given as follows: Section I contains the introduction about semantic image segmentation, Section II analysis different semantic image segmentation techniques, Section III explains the proposed methodology, Section IV illustrates the experimental results of the proposed methodology, Section IV concludes the research work.

II. RELATED WORK

An ontology-based model [12] was proposed for collaborative semantic annotation of images. In this model, annotators annotate the images with the help of keywords and then keywords were weighted using the weighting model based on their frequency of occurrence and terms rank. This model used keywords where semantically enriched ontologies were explored for image retrieval. However, there is a trade-off between complexity and performance of the ontology-based model.

A hierarchical segmentation algorithm [13] was proposed for image segmentation. Initially, this algorithm started with a very fine segmentation and a cascaded of boundary classifiers were used in the merged regions. A cascaded of boundary classifiers was constructed and it generates increasingly coarse image partitions by merging regions preserved by previous stages. A probabilistic model was applied in each stage that was adapted to the scale at which it operates. This architecture is called as an Image Segmentation by Cascaded Region Agglomeration (ISCRA). However, the performance of ISCRA is its dependence on the initial segmentation.

A novel framework called as a Multi-Class Multi-Scale (MCMS) series contextual model [14] was proposed for image segmentation. From multiple objects and at different scales of an image, the MCMS used contextual information to learn the discriminative models in a supervised setting. It combined the inter-object and cross-object information into one probabilistic framework. It captured geometrical dependencies and relationship among multiple objects. It enhanced the performance of object segmentation and provided a coherent segmentation of multiple objects. However, this framework has a high computational complexity problem.

An efficient semantic image segmentation model [15] was proposed with multi-class ranking prior. It utilized maximum margin based Structural Support Vector Machine (S-SVM) which integrated multiple levels of cues to satisfy the ambiguity of appearance similarity. Then a novel multiclass ranking based global constraint was proposed to detain the object classes to be assumed when labeling regions within an image. In order to enable a joint inference of labeling within an image with better consistency, inter-class co-occurrence statistics was introduced as pairwise constraint and combined them with the prediction from global and local cues based on S-SVMs framework. However, it failed to integrate multi-source cues which contain complementary information for image segmentation.

A hybrid graphical model [16] was proposed for semantic image segmentation. A hybrid Hierarchical Conditional Random Field (HCRF) was used to capture a non-causal relationship. It produced initial semantic sub-scene predictions. A Bayesian Network (BN) model was utilized to model contextual interactions for each semantic sub-scene in the form of class statistics from its neighboring regions. The conditional probabilities of neighboring regions were automatically learned from training data. The learned BN structure was utilized to encode the structure of contextual dependencies for sub-scenes in the initial predictions to generate final refined predictions.

Ontology-Based Semantic Image Segmentation (OBSIS) [17] was proposed using mixture models and multiple Conditional Random Fields (CRFs). The dimensionality of features was reduced by transforming low-level visual space into an intermediate semantic space through a Dirichlet process mixture model. Then weighted the features and these were learned independently using CRFs. Hence the segmentation of images was converted into a classification task. By these processes, the human can understand the images through the combination of different context models, cues and rule-based learning of the ontologies. The OBSIS method was failed to segment touching objects with similar features.

A Shuffling Convolutional Neural Networks (SCNNs) method [18] was proposed for semantic segmentation of aerial images. This proposed method introduced shuffling operator into semantic segmentation of aerial images, upon which two networks were proposed called as Naïve-SCNN and Deeper-SCNN which is a naïve version and deeper version of SCNN. These two methods were adapted to detect small objects in images. In addition to that, Field-of-View (FoV) was proposed to enhance the prediction of small objects in images. Sometimes, Naïve-SCNN is not getting a smooth result.

A semantic image segmentation model called Expectation-Maximization (EM) based semi-supervised model [19] was proposed for efficient semantic image segmentation. With an aid of large-scale weakly labeled datasets, EM-based semi-supervised model enhanced the semantic segmentation of histopathological images. This model restrained by an approximated prior distribution to extract useful representations from a huge volume of weakly labeled images developed from low-magnification annotations. Even though it improved the performance of a model on a limited fully annotated dataset, it might be challenging to get the perfect segmentation for high-grade areas.

For semantic image segmentation, a semantic segmentation scheme [20] was presented. It used Laser Detection and Ranging (LiDAR) and high-resolution aerial imagery data. This scheme combined Multi-Resolution Segmentation (MRS) and multi-filter Convolutional Neural Network (CNN) to segment the images semantically. The multi-filter CNN performed semantic labeling with the aid of multi-modal data fusion where high-resolution optical imagery and the LiDAR were combined. Furthermore, MRS was further used to describe object boundaries which minimize the salt-and-pepper artifacts. However, there remains some amount of salt-and-pepper artifacts on the object boundaries and patch edges.

III. METHODOLOGY

In this section, the process of ontological taxonomic knowledge representation with CHM-IOLDNN is described in detail. The ontological taxonomic knowledge representation [15] defines the semantic relation between the concepts in the images. A knowledge model must contain a large number of distinct and diverse relations among concepts. In order to define complex types of semantic relations in ontology, a fuzzification concept is introduced in the ontology. Then a relation is constructed based on the fuzzy taxonomic relations. The constructed semantic relations are given as additional input to CHM-IOLDNN which can segment the images with the consideration of semantic relation.

A. *Ontology-Based Contextual Knowledge Representation*

Ontologies are suitable for expressing the semantics of image content in a machine-processable representation that allows manual or automatic analysis and further processing of the extracted semantic descriptions. The ontologies can be formalized as:

$$O = \left\{C, \left\{R_{xy}\right\}\right\}, where\ R_{xy}: C \times C \to \{0,1\} \quad (1)$$

where O is an ontology, C is the set of concepts in image described by the ontology, x and y are two concepts x,y∈C and R_xy is the semantic relationship among these concepts. The semantic relations among the concepts are obtained from MPEG-7 MDS [21] which contains all types of semantic relations.

The ontology-based contextual knowledge representation model is formed based on a set of concepts and relations between them, which is given as input to the CHM-IOLDNN [8] for semantic image segmentation. In this work, three types of semantic relations such as specialization relation, the part of relation and the property of relations are used. The semantic relation in the ontology defines specific kinds of relationships between any two concepts.

The semantic relation R_{xy} either relates or does not relate a pair of concepts x, y with each other. A taxonomic relation is used to construct knowledge representation where any type of relation can be included in the ontology. In order to improve the ontology-based contextual knowledge representation, the crisp semantic relation can be modeled as fuzzy ordering relations. The fuzzy ordering relations can be combined for the generation of a meaningful fuzzy taxonomic relation. Based on the fuzzy ordering relation, the ontologies can be re-formalized as:

$$O_F = \left\{C, \left\{r_{xy}\right\}\right\}, where\ r_{xy} = F\left(R_{xy}\right): C \times C \to [0,1] \quad (2)$$

where O_F is a fuzzified ontology, r_{xy} denotes a fuzzy relation amongst two concepts $xy \in C$. In the fuzzy case, a fuzzy semantic relation relates a pair of concepts x, y with each other to a given degree membership. The fuzzy semantic relation r_{xy} values lies within 0 to 1 value. A fuzzy set F on C is described by a triangular membership function $\mu_F: C \to [0,1]$. The fuzzy set F on C is given as follows:

$$F = \sum_{i=1}^{n} \frac{c_i}{w_i} = \left\{\frac{c_1}{w_1}, \frac{c_2}{w_2}, \dots \frac{c_n}{w_n}\right\} \quad (3)$$

where $n = |C|$ is the cardinality of set C and concept $c_i \in C$. The membership degree w_i defines the triangular membership function $\mu_F(c_i)$, i.e., $w_i = \mu_F(c_i)$. A fuzzy relation on C is a function $r_{xy}: C \times C \to [0,1]$ and its inverse relation is defined as $r_{xy}^{-1} = r_{xy}$. Based on the relation r_{xy} and for purpose of semantic image segmentation, the following relation T is constructed with the use of the above set of fuzzy taxonomic relations: S_x, X and Xr:

$$T = Tr^t(S_x \cup X^{-1} \cup Xr^{-1}) \quad (4)$$

where, the high values of $S_x(x, y)$ imply that the meaning of q approaches the meaning of x which means that when an image is semantically related to y, then its most probably related to x as well. On the other hand, as $S_x(x, y)$ decreases, the meaning of y becomes narrower than the meaning of x, which means than an image's relation to y will not imply a relation to x as well with a high probability or to a high degree. Similarly, the degrees of the other two relations can also be interpreted as degrees or conditional probabilities of implied relevance. All types of semantic relations along with their inverses are contained in MPEG-7 MDS. Sometimes, the inverses are more meaningful than semantic relations. The relation part $X(x, y)$ is defined as x part y if and only if y is part of x. Likewise, for the property relation Xr, its inverse is selected. Alternatively, following the definition of the specialization relation $S_x(x, y)$, x is specialization of y if and only if y is a specialization meaning of x.

According to these roles and semantic interpretations of S_x, X and Xr, a relation T is constructed. In the relation T, transitive closure Tr^t is required in order for T to be taxonomic, as the union of transitive relations is not necessarily transitive. The constructed T is given as additional input to the CHM-HHCRF-IOLDNN which adjusting the segmentation results based on the semantic relation between the concepts in taxonomy.

IV. Results and Discussion

The performance of CHM-HHCRF-IOLDNN and OCHM-HHCRF-IOLDNN are evaluated through experimental studies in terms of class accuracy, pixel accuracy, F-measure and G-mean. For the experimental purpose, Stanford background dataset and Weizmann dataset are used.

The Stanford background dataset is an outdoor scene labeling dataset with multiple classes which consist of 715 images from which 572 images are used for training and 143 images are used for testing. The Weizmann dataset is a binary segmentation dataset which consists of 328 images from which 164 images are used for training and 164 images are used for testing.

A. Sandford background dataset

The class-average accuracy and pixel-wise accuracy values of Contextual Hierarchical Model- Higher order Hierarchical Conditional Random Field- Improved Optimized Logistic Disjunctive Normal Networks (CHM-HHCRF-IOLDNN) and ontology-based contextual knowledge representation with CHM-HHCRF-IOLDNN (OCHM-HHCRF-IOLDNN) are given in Table 1.

Table 1. Performance of Segmentation Methods on Stanford Background Dataset Using Class-Average Accuracy and Pixel-wise Accuracy

Method	Class Accuracy	Pixel Accuracy
CHM-HHCRF-IOLDNN	95.07%	96.45%
OCHM-HHCRF-IOLDNN	98.56%	98.79%

In Figure.1, comparison metrics class-average accuracy and pixel-wise accuracy is taken in X-axis and the range of their values is taken in Y-axis. The class accuracy of OCHM-HHCRF-IOLDNN is 3.7% more than CHM-HHCRF-IOLDNN. The pixel accuracy of OCHM-HHCRF-IOLDNN is 2.4% more than the CHM-HHCRF-IOLDNN. From this analysis, it is proved that the proposed OCHM-HHCRF-IOLDNN has high class accuracy and pixel accuracy than the CHM-HHCRF-IOLDNN method.

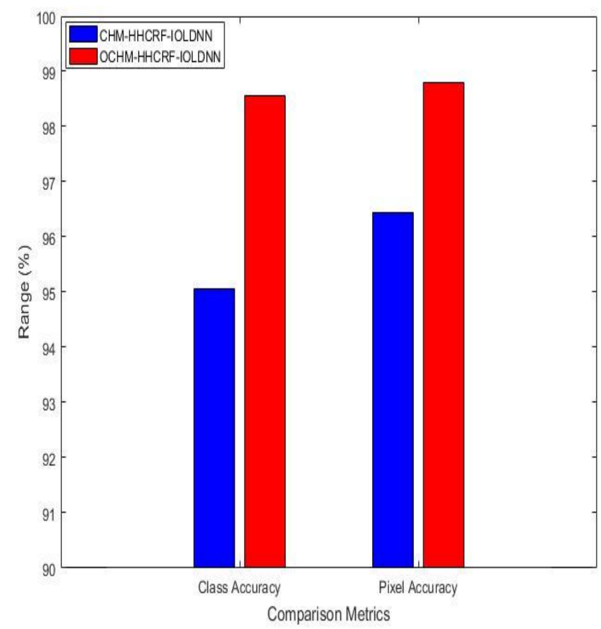
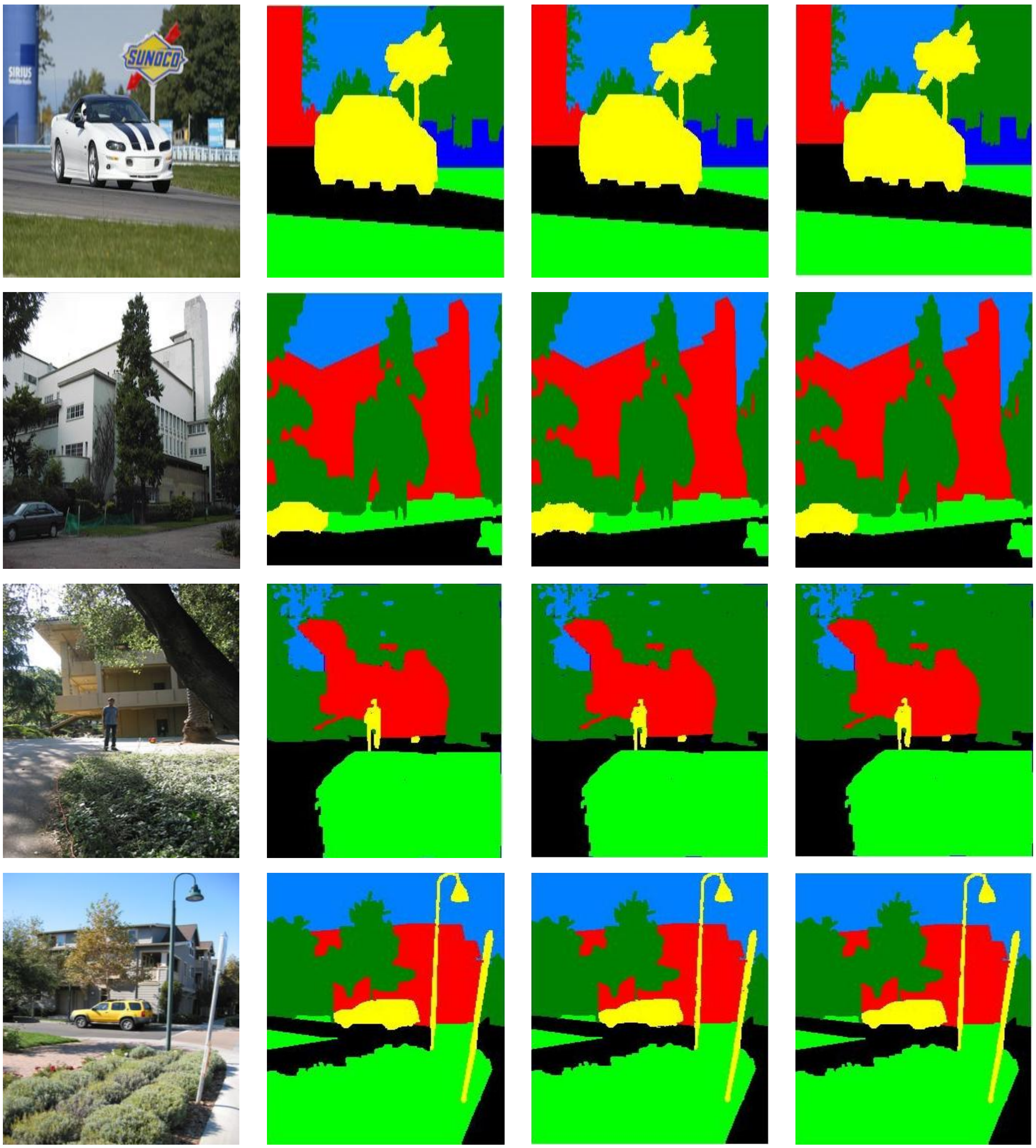


Fig. 1 Comparison of Class Accuracy and Pixel Accuracy on Stanford background dataset

Figure.2 shows the comparison of class accuracy between CHM-HHCRF-IOLDNN and OCHM-HHCRF-IOLDNN on Stanford background dataset. The ontology-based contextual representation defines a semantic relation between the concepts in images which are used to adjust the semantic and labeling results. The specialization relation, the part of relation and the property of relations are taxonomic relation which effectively improves the class-average accuracy for semantic image segmentation. The pixel-wise accuracy is improved by using the fuzzy taxonomic relation in CHM-HHCRF-IOLDNN.

The performance of CHM-HHCRF-IOLDNN and OCHM-HHCRF-IOLDNN for 4 sample images of Stanford background dataset is shown in Figure.2 The first column shows the input images which have 256×256 resolution. The second column shows the ground truth image of the input image. The third column shows the output of CHM-HHCRF-IOLDNN method and the fourth column shows the output of OCHM-HHCRF--IOLDNN method.



Legends: Object Road Grass Building Sky Divider Tree

B. Weizmann dataset

The performance analysis results of CHM-HHCRF-IOLDNN and OCHM-HHCRF-IOLDNN on Weizmann dataset is given in Table 2. The performance of CHM-HHCRF-IOLDNN and OCHM-HHCRF-IOLDNN for 4 sample images of Weizmann dataset is shown in Figure. 3 The first column shows the input images which have 256×256 resolution. The second column shows the ground truth image of the input image. The third column shows the output of CHM-HHCRF-IOLDNN method and the fourth column shows the output of OCHM-HHCRF--IOLDNN method.

Table.2 Performance of Segmentation Methods on Weizmann Dataset Using F-Measure and G-Mean

Method	**F-Measure**	**G-Mean**
CHM-HHCRF-IOLDNN	94.89%	98%
OCHM-HHCRF-IOLDNN	97.94%	99.45%

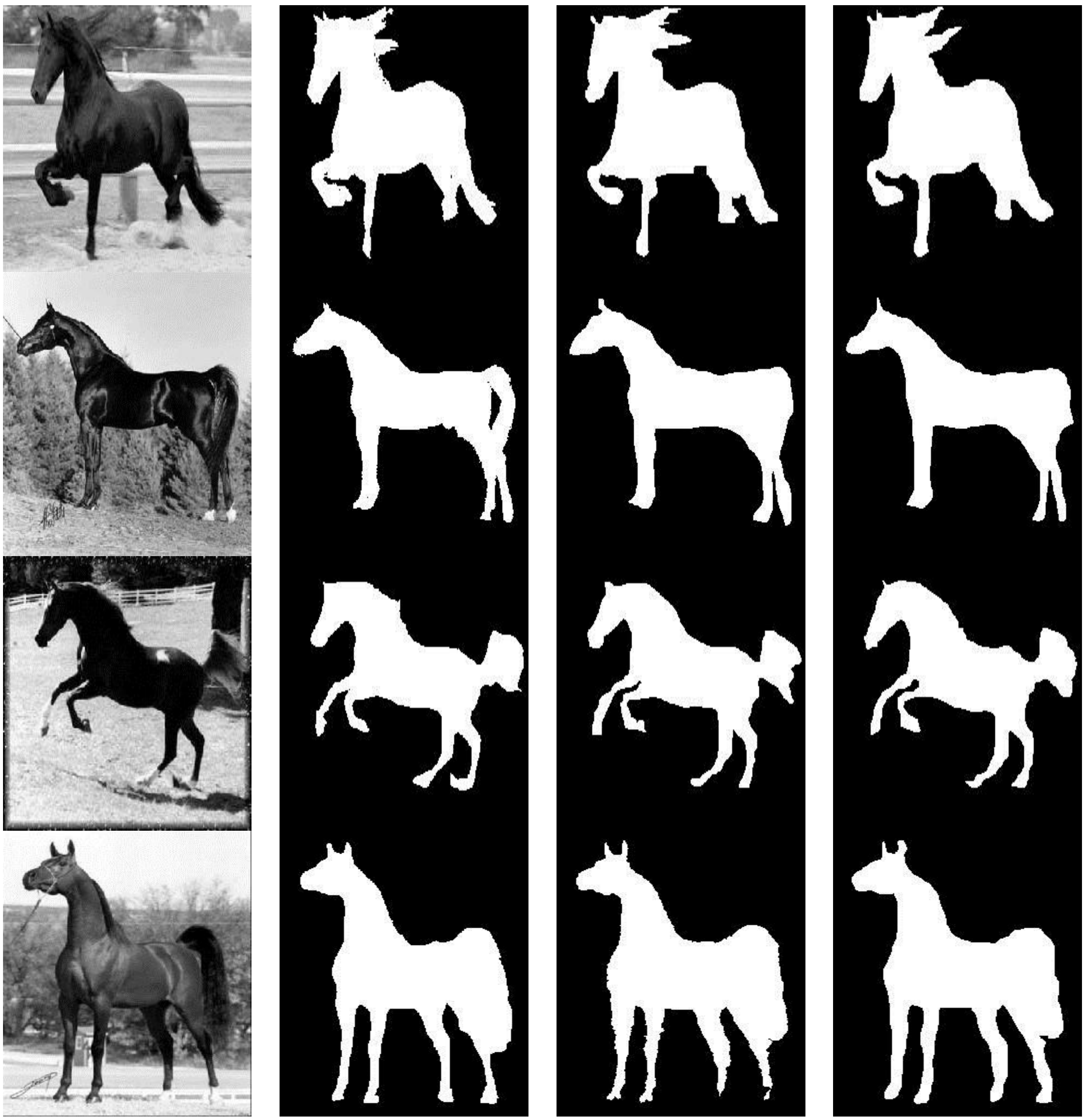


Figure.3 Test Samples of Semantic Image Segmentation of Weizmann Dataset.

From Table 2 and Fig. 4, it is found that the proposed OCHM-HHCRF-IOLDNN has better F-Measure and G-Mean than CHM-HHCRF-IOLDNN method. The constructed ontology defines the semantic relation between the concepts in images using the specialization relation, the part of relation and the property of relations. These relations are considered in the semantic image segmentation based on CHM-HHCRF-IOLDNN. It improves the F-Measure value of OCHM-HHCRF-IOLDNN.

The G-Mean value of OCHM-HHCRF-IOLDNN is improved by analyzing the complex types of concepts in images using the fuzzified taxonomic relation. The comparison metrics F-Measure and G-Mean is taken in X-axis and their range of values is taken in Y-axis. The F-Measure value of OCHM-HHCRF-IOLDNN is 3.2% more than CHM-HHCRF-IOLDNN. The G-Mean value of OCHM-HHCRF-IOLDNN is 1.5% more than CHM-HHCRF-IOLDNN. From this analysis, it is proved that the proposed OCHM-HHCRF-IOLDNN has high F-Measure and G-Mean than the CHM-HHCRF-IOLDNN method.

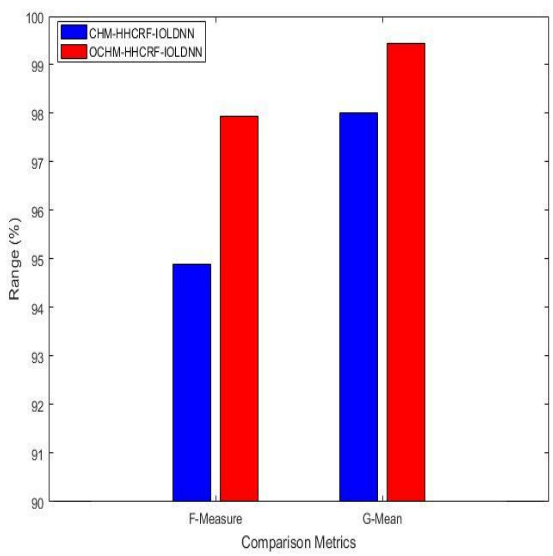


Figure.4 Comparison of F-Measure and G-Mean on Weizmann dataset

V. CONCLUSION

The main contribution of this paper is to provide efficient semantic image segmentation by proposing ontology-based contextual knowledge representation with CHM-HHCRF-IOLDNN. Initially, ontologies are constructed based on the semantic relation between the concepts in the images. Then a fuzzification is introduced in ontology to define the complex types of relations between the concepts in images. The specialization relation, the part of relation and the property of relations are fuzzified using triangular membership function which more effectively defines the complex types of relations. Based on the fuzzified taxonomic relation, a relation is constructed which is used in CHM-HHCRF-IOLDNN to segment the images. The experimental results show that the proposed OCHM-HHCRF-IOLDNN has better class accuracy, pixel accuracy, F-measure and G-mean than the other segmentation method.

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