Energy-Efficient Object Detection using Semantic Decomposition

Priyadarshini Panda, Swagath Venkataramani, Abhronil Sengupta, Anand Raghunathan, Fellow, IEEE and Kaushik Roy, Fellow, IEEE

Abstract—Machine-learning algorithms offer immense possibilities in the development of several cognitive applications. In fact, large scale machine-learning classifiers now represent the state-of-the-art in a wide range of object detection/classification problems. However, the network complexities of large-scale classifiers present them as one of the most challenging and energy intensive workloads across the computing spectrum. In this paper, we present a new approach to optimize energy efficiency of object detection tasks using semantic decomposition to build a hierarchical classification framework. We observe that certain semantic information like color/texture are common across various images in real-world datasets for object detection applications. We exploit these common semantic features to distinguish the objects of interest from the remaining inputs (non-objects of interest) in a dataset at a lower computational effort. We propose a 2-stage hierarchical classification framework, with increasing levels of complexity, for faster and more energy-efficient object detection. Our experiments on the Caltech101/CIFAR10 dataset show that the proposed method yields 1.93x/1.46x improvement in average energy, respectively, over the traditional single classifier model.

Index Terms—Energy-Efficiency, Neural Networks, Hierarchical Classification, Semantic (Color/texture) Decomposition.

I. INTRODUCTION

Object detection is one of the core areas of research in computer vision [1]. It is extensively used for photo and video search across computing platforms and has been successfully deployed in many real-world world applications such as Google Image Search [2], [3], Google Now speech recognition [4], [5], and Apple Siri voice recognition [6] among others. Machine-learning classifiers have proven to be very useful for implementing such detection tasks [7]. A detection task is basically a classification problem of distinguishing an object of interest from a host of input data. Traditionally, a single complex classifier model (shown in Fig. 1 (a)) is used to perform detection. Here, all the inputs are processed through the single model to detect the object of interest. However, in order to scale to more challenging object detection problems, the classifier models must become larger, which implies an increase in computational resources. With computational efficiency becoming a primary concern across the computing spectrum, energy-efficient object detection is of great importance.

Interestingly, we note that in a real world dataset, a major portion of input images have some characteristic broad semantic features like color, texture etc. that are common to the object of interest. Consider the simple example of detecting a red Ferrari from a sample set of vehicle images consisting of motorbikes and cars. The first intuitive step is to recognize all red vehicles in the sample and then look for a Ferrari-shaped object from the sub-sample of red vehicles Thus, we can reduce and simplify the original sample set by utilizing the semantic information as we progress towards the primary object detection task. This simplification can potentially reduce the compute effort. Based on this idea, we introduce semantic decomposition of inputs into characteristic broad features, like color (red) or shape (car) in the above example, and using the representative semantics to build a hierarchical classification framework, with increasing levels of complexity, for faster and more energy-efficient object detection.

Fig. 1 illustrates our methodology. In the traditional approach shown in Fig. 1(a), input training examples are used to train the classifier (denoted as Classifier X) to separate data into two categories or classes: objects of interest that we are trying to detect (Class 2) and clutter or non-object of interest (Class 1). At test time, data instances are assigned...
to one class or the other depending on their labels. The computational effort in terms of energy and time to process every test instance depends on the complexity of the network i.e. the total number of weights and the neurons composing the classifier. In the example of Fig. 1(a), a single classifier clearly needs to be highly complex (more hidden neurons and hence, more synapses) in order to separate the classes with high accuracy. However, this leads to high computational effort for not only the test instances that have common semantic between the two classes but also the ones that do not share common features across the class labels.

In contrast, Fig. 1(b) shows our approach where we create a semantically decomposed framework with multiple classifiers (Y and X) with varying levels of complexity. Certain images in the dataset have a common semantic information representative of the object of interest shown by the shaded region in Fig. 1. Classifier Y is trained to identify all those instances that share the particular semantic with our object of interest (Class 2). It receives important yet simple semantically decomposed characteristics like color, edges, etc. from the input sensor data. The decomposed input features are simpler and easy to process than the original input image. Thus, the classifier in the first stage (Y) of the proposed framework are small scale (or less complex with few neurons and weights). The complex classifier X is then enabled for all those instances that have the semantic information that model Y is trained to detect. Hence, a significant portion of clutter (Class 1) are filtered out or eliminated at the first stage in this process. The second stage X, same as the complex classifier in the traditional approach, tries to detect the object of interest from the original input image. This approach can save time and energy, since all data instances need not be processed by the more complex traditional classifier. Please note that since the proposed methodology adds an extra classifier (first stage) into the overall classification framework, the additional cost overhead for the instances that are processed by both stages has to be taken into account in the computational cost.

In order to observe maximum benefits and overcome the cost penalty (that the addition of first stage imposes), it is evident that the input dataset should have significantly larger clutter fraction than the objects of interest. Fortunately, in many useful detection applications, only a small fraction of the input dataset has relevant objects of interest. For instance, in security video based image detection aims at recognizing suspicious person movement from enormous amount of input data. However, only a marginal fraction of the sensor data has the relevant object of interest (suspicious person in this example). In [8], the authors have quantitatively established that in a wide range of video-based object detection datasets, only 5% of the input data contains the relevant objects of interest. Our approach exploits this disproportionate distribution of input data to obtain compute-efficiency. The amount of time and energy saved also depends on how appropriately we decompose the input data or extract the common features such that we can reject as much clutter as possible in the first stage at very low complexity.

In summary, the key contributions of this paper are as follows:

- Given an object detection task, we propose a systematic methodology to construct a semantically decomposed framework that exploits the common semantic information in the input images to perform faster and energy-efficient classification. The hierarchical framework has iso-accuracy as that of the baseline classifier.
- The initial stages of the framework filter out clutter data based on semantic information. In this work, we use color and texture as the distinctive semantic traits to carry out object detection. We use Hue-Saturation-Value (HSV) transformation [33] and Gabor filtering [34] to extract color and texture components, respectively.
- We propose an algorithm to select the optimal color/textured relevant to the object of interest. This enables us to construct the initial stage of the framework with lower computational complexity and reduce the additional cost penalty that the first stage imposes. The algorithm determines the best AND/OR configuration of classifiers in the initial stage to optimize the computational cost at iso-accuracy.
- We also present a training methodology to construct the semantically decomposed framework.
- We demonstrate the efficacy of our proposed approach on two natural image datasets: Caltech101/ CIFAR10. We show that the semantic decomposed classification framework with ANNs provides 1.93x/1.46x reduction in average energy through hardware implementation on a 45nm SOI process.

The rest of the paper is organized as follows. In Section II, we discuss related work. In Section III, we present the basics on HSV and Gabor filtering used for semantic decomposition on input data. In Section IV, we describe our approach to construct the semantically decomposed framework discussing all efficiency and accuracy optimization criterion. In Section V, we discuss the methodology to train and test the semantic framework. In Section VI, we present the experimental methodology and benchmarks. We discuss the results in Section VII and conclude in Section VIII.

II. RELATED WORK

On the algorithmic front, using multiple classifiers for increasing learning accuracy is an active area of research [12], [14], [15], [17]. A class of work in ensemble based learning [9]–[11] exploit the idea that different classifiers can offer complementary information about patterns to be classified which can be used to improve the effectiveness of the overall recognition process. Ensemble learning techniques, for instance Boosting [12] and Bagging [13], use multiple predictive models to produce an aggregate model whose prediction accuracy is better than individual models used alone. The Viola-Jones algorithm used for face detection is another classic example [18]. It comprises a 21-stage cascade of simple detectors that operate on multiple patches of an image. At each stage, if an image patch matches a particular pattern, it is passed on to the next stage for classification; if not, it is rejected early in the chain. The main motivation behind the above algorithmic techniques is to obtain an improvement in
accuracy. However, using them to reduce energy and runtime has received attention only in the recent past [16]. The use of multiple classifiers in our proposed methodology is entirely driven by energy-efficiency and reduced computational complexity.

Past research in building energy-efficient neuromorphic systems have considered application-specific solutions [19], [20]. In [21], the authors have proposed a scalable effort classification framework consisting of a cascaded chain of biased classifiers with increasing complexity that can dynamically adjust the compute effort depending on the input data. The consensus between the classifier’s outputs is used to decide if classification can be terminated at an earlier stage. The methodology that we propose in this paper is complementary to the concept of cascading classifiers. However, the novelty of our work arises from the fact that we leverage the semantic information in the input data to obtain efficiency and reduced testing complexity. Please note that though our training method draws inspiration from [21], our method has different focus, design and evaluation strategies.

Other popular approaches that have been explored to lower the compute effort of the network is based on approximate computing [22]–[24]. Exploiting the inherent error resilience of a system, a variety of approximate hardware [25], [26] and software [27], [28] techniques have been proposed to achieve reduced computational complexity. Substantial improvements in classification tasks have also been obtained by combining or integrating the outputs of classification techniques [29]–[31]. However, these techniques provide an explicit trade-off between efficiency and quality of results [32]. Our approach, on the other hand, provides energy savings, while maintaining classification accuracy.

Overall, the main focus of this work is to extract energy efficiency for object detection application while maintaining the output quality. Our proposed systematic method extracts the appropriate semantic information characteristic of the objects of interest, thereby giving us less complex classifiers which is reflected in the low computational cost.

### III. Semantic Decomposition of Input Data

In our proposed methodology, semantic decomposition is a very significant stage. In this stage, semantics such as texture or color components representative of the input image are extracted using appropriate image processing techniques. In this work, we use color and texture information individually in a set of experiments described in Section VI as the first step of eliminating objects that do not share common semantic information. We use Hue-Saturation-Value (HSV) transformation [33] and Gabor filtering [34] to extract color and texture components, respectively. The extracted components are then used as training instances to train the simpler (or less complex) classifiers in the first stage that filter out clutter from the objects of interest based on the absence of relevant semantic information. While we use color and texture as characteristic semantics, please note that other semantics can also be used with the proposed methodology.

A. Color detection using HSV transformation

The HSV color space has good capability of representing the colors of human perception [33]. The formula for conversion of RGB color space into HSV is shown below:

\[
H = \arccos\left(\frac{(R-G) + \frac{R-B}{2}}{[\sqrt{(R-G)^2 + (R-B)(G-B)}]^2}\right), \text{if} (B \leq G)
\]

\[
S = \frac{\max(R,G,B) - \min(R,G,B)}{\max(R,G,B)}
\]

\[
V = \frac{\max(R,G,B)}{255}
\]

A regular colored image is represented by the RGB components. We use the above formula to extract different color components of an image based upon the H, S and V values. For example, the main colors in HSV component threshold range is shown in Table I.

After applying an HSV transformation, an image in the HSV space is much smaller as compared to the RGB space. For example, a 300x200 pixel sized image in RGB the space has 300x200x3 values while the same image transformed into the HSV has 300x200 values of relevant color information. Referring to the red Ferrari example, appropriate HSV transformation will extract the red components, depending upon the range specified in Table I, from the sample of vehicle images. The extracted feature vector is the input to the first stage classifier in the framework which is trained to recognize all inputs that have significant red component in them. Please note that we need to take into account the additional cost of the HSV transformation for calculating energy costs [35].

B. Texture abstraction using Gabor Filtering

Besides color, a useful set of features commonly used for image segmentation relate to texture. Gabor filters are a popular tool for the task of extracting these spatially localized spectral features [34], [36]. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a complex sinusoidal plane wave, defined as:

\[
G(x,y) = \frac{f^2}{\pi \gamma \eta} \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2 \sigma^2}\right) \exp(j2\pi f x' + \phi)
\]

\[
x' = x \cos \theta + y \sin \theta
\]

### Table I

| Color | H | S | V |
|-------|---|---|---|
| White | - | ≤0.1 | <0.1 |
| Black | - | - | <0.1 |
| Red | ≤30, >330 | 0.1 ≤ S ≤ 1 | 0.1 ≤ V ≤ 1 |
| Yellow | >30, ≤90 | " | " |
| Green | >90, ≤150 | " | " |
| Cyan | >150, ≤210 | " | " |
| Blue | >210, ≤270 | " | " |
| Magenta | >270, ≤330 | " | " |

The proposed methodology that we propose in this paper is complementary to the concept of cascading classifiers. However, the novelty of our work arises from the fact that we leverage the semantic information in the input data to obtain efficiency and reduced testing complexity. Please note that though our training method draws inspiration from [21], our method has different focus, design and evaluation strategies.
\[ y' = -x \sin \theta + y \cos \theta \] (6)

where \( f \) is the frequency of the sinusoidal factor, \( \theta \) represents the orientation of the normal to the parallel stripes of a Gabor function, \( \phi \) is the phase offset, \( \sigma \) is the standard deviation of the Gaussian envelope and \( \gamma \) is the spatial aspect ratio which specifies the ellipticity of the support of the Gabor function.

In this work, we have used 2D Gabor filters to extract spatial features, specific to a particular image, at different frequencies and orientations. An appropriately designed filter will extract useful information such as spots and edges. But this would also require us to have separate unique filters for every image. In order to have a generic approach, we have used the filter bank approach as proposed in [37], [38] where filters are generated using a ‘filter bank’ which are then applied to every image in the dataset resulting in characteristic textural information. Then, we can look at the relationship between Gabor responses of different images for classification purposes.

Gabor filtering also results in dimensionality reduction of the original image and results in an input vector even smaller than that obtained from HSV transformation [38]. The considerable decrease in input vector size enables the scaling down of the first stage in the framework. However, Gabor filtering itself is computationally expensive due to complex convolution operations. Hence, as in HSV, this additional cost of processing also has to be taken into account for energy computations.

IV. SEMANTICALLY DECOMPOSED OBJECT DETECTION

In this section, we present our structured approach to design the hierarchical framework of classifiers. Optimum semantic selection and conditional activation of the classifier in the second stage form the bases of the framework. While there exists a suite of machine-learning classifiers like Support Vector Machines, Decision Trees, Neural Networks etc. suitable for object detection, we will focus on a particular class: Artificial Neural Networks (ANNs) to validate the proposed methodology for object detection. Please note that the semantically decomposed framework can be applied on other classification algorithms as well to lower the compute effort. In the rest of the paper, the terms ‘Semantically decomposed framework’ and ‘Hierarchical framework’ have been used interchangeably.

A. Semantic based Elimination: Concept

Fig. 2 (a) shows the conceptual view of the framework. All ANN models in both the traditional and hierarchical structure are learnt using the same algorithm and training data. In the traditional approach, as shown in Fig. 1(a), a single ANN model processes the RGB components of the image during training and classification. In the 2-stage framework (Fig. 2(a)), each of the ANNs in the first stage are computationally efficient as they are trained on the optimal simple semantic feature vectors extracted from the original RGB image. The ANN in the second stage has a higher complexity on account of being fed the original RGB image for classification. Depending on the output of the ANNs in the first stage, the second stage is enabled. This results in significant power savings due to conditional activation of the network in the second stage. The final classifier, same as the NN in the traditional structure, with the highest complexity makes sure that any clutter data that were passed onto the stage by the former ANNs due to misclassification are properly discarded or, classified as clutter in this stage, thereby maintaining the same classification accuracy as the traditional single classifier. Besides the ANNs in the hierarchy, the setup also contains an activation threshold module (Fig. 2(a)). This module decides if the second stage should get enabled or not to determine the final output of the hierarchy for a given input image. Note that if the input is the desired object we are trying to detect, it will always be passed to the second stage. Then, the output of the hierarchy is based on the classification result of the second stage. Only when any clutter image is presented, the module then decides based on the following two criteria:

- If the classifiers in the first stage predict based on the semantic vector that the input presented is a clutter image, the second stage is not enabled and the output of the framework is a label corresponding to clutter.
- If the classifiers in the first stage produce a sufficient confidence level on the input image’s semantic vector, the second stage is enabled. The second stage then processes the original RGB image corresponding to the initial input presented. The framework’s final output is a label based on the result of the second stage.

B. Optimal Semantic Selection

The most important question that needs to be answered is how we select the appropriate semantics to construct the first stage configuration of the hierarchical structure. As mentioned earlier, addition of first stage imposes a cost penalty for inputs that need activation of both stages in the framework for correct classification (Fig. 2(a)). In contrast, in the traditional approach (Fig. 1(a)), only the single ANN needs to be enabled to get the final result. Thus, optimal semantic selection is key to obtaining a first stage with the lowest complexity so that the
overall cost penalty can be reduced considerably. To make our proposed approach more systematic, we devise an algorithm that recognizes the most optimum features and constructs a 2-level OR-AND configuration of the first stage for the most favorable classification results. Fig. 2(b) shows an example of the 2-level OR-AND first stage configuration for a given input dataset with 3 optimal semantic features. The given configuration implies that the second stage is only enabled when the first stage detects either Semantic 1 or 2 (OR) in combination with Semantic 3 (AND). In other words, the final ANN is enabled if ANN 3 and either of ANN 1 or 2 produce sufficient confidence level for a given input.

1) Efficiency and Accuracy Optimization with OR-AND configuration: To better understand the need for 2-level OR-AND configuration, consider the example shown in Fig. 3. Observe that the objects of interest can be characterized by two different semantic features. Hence, we need two different ANNs trained on two separate feature vectors in the first stage of the hierarchy. Fig. 3(a) shows that certain instances in the objects of interest have one semantic in common while the rest have the second semantic. So, we can choose the OR operation where the second stage/final classifier is enabled when we get a desired output from any one of the NNs in the first stage. In other words, final NN is enabled if one or the other semantic is identified from the input image. If the operation is set to be AND here, certain objects of interest will be rejected or misclassified in the first stage that will result in a significant decline in accuracy. On the other hand, in Fig. 3(b), both semantics are present in all the instances of objects of interest. While an OR would give a good result i.e. all objects of interest will be classified by the first stage and passed to the final classifier, however, the first stage would also pass a lot of clutter. This in turn would enable the final classifier for all the clutter passed resulting in a decline in efficiency. Thus, we need to set the activation as an AND operation where the final NN is enabled for inputs having both semantics i.e. we get a good confidence level for both the NNs in the initial stage. Fig. 3(b) clearly illustrates that the AND operation filters out a lot of clutter in the initial stage before forwarding to the final classifier. Thus, it is evident that while AND improves the efficiency of the classifier, OR increases the accuracy of the semantically decomposed framework. So, the semantic selection algorithm constructs the most optimal first stage OR-AND configuration that yields lowest computational cost with minimal loss in output quality in comparison to the baseline/traditional single classifier.

2) Adding ANNs or classifiers in first stage: While adding a new ANN to the first stage configuration, the algorithm calculates the overall gain obtained with conditional activation accounting for the additional penalty of the first stage. Consider a baseline ANN with computational cost $N_{\text{orig}}$ per instance. Let $f$ be the fraction of inputs that are filtered out or eliminated at the first stage. Let the computational cost of the first stage configuration of the semantically decomposed framework be $N_{\text{initial}}$. The following condition (Eq. 7) should be satisfied to improve the overall efficiency of the hierarchical framework:

$$N_{\text{initial}} + (1 - f).N_{\text{orig}} < N_{\text{orig}}$$

(7)

$$G = N_{\text{orig}} - [N_{\text{initial}} + (1 - f).N_{\text{orig}}]$$

(8)

The left hand side of Eq. 7 represents the overall gain in efficiency with the semantically decomposed framework, which is the summation of first and second stage complexities. The second stage has a reduced complexity on account of conditional activation only for those fraction of inputs passed to that stage. This should be greater than the right side of Eq. 7 which denotes the original cost of the baseline/traditional single ANN classifier without any penalty from the addition of first stage. The difference of the left side from the right side is the overall gain ($G$) as shown in Eq. 8.

3) Semantic Selection Methodology: Algorithm 1 shows the pseudo code for selecting the optimal semantics and constructing the 2-level OR-AND configuration for the first stage of the semantically decomposed framework. The process takes the baseline/traditional single ANN $N_{\text{orig}}$, training dataset $D_{tr}$ and the semantic feature search space as input and produces the optimal first stage $N_{\text{initial}}$ with appropriate OR-AND configuration. First, we train $N_{\text{orig}}$ on $D_{tr}$ and obtain the accuracy $Q$ (line 2). Next, we iteratively traverse through the semantic feature space selecting the feature (or combination of features) that improves the gain while maintaining the quality constraint (lines 3-20). The procedure terminates if adding a particular feature to the first stage doesn’t improve the gain of the existing first stage configuration (line 8).

Initially, we search through the vector space and check the quality and gain constraints for each semantic vector (lines 3-11). The semantics that improve the overall gain, calculated

![Diagram](image-url)
Algorithm 1 Pseudo code for optimal semantic selection and 2-level OR-AND construction of first stage

Input: Baseline classifier $N_{\text{orig}}$, training dataset $D_{tr}$, # features in the search space $N$

Output: First stage NN configuration: $N_{\text{initial}}$

1: initialize $N_{\text{initial}}$ = NULL, pairwise = FALSE, $G_0$ = $\epsilon$
2: Train $N_{\text{orig}}$ using $D_{tr}$ and obtain the accuracy, $Q$.
3: for $i = 1 : N$ // for each feature vector in the search space
4: Train a NN ($N_i$) on the feature vector $i$ using $D_{tr}$ and obtain accuracy, $Q'$ for the hierarchical framework with $N_i$ as first stage and $N_{\text{orig}}$ as second stage.
5: if $(Q - Q') < \epsilon$ // if quality constraint is met
6: $N_{\text{initial}} = N_i$ AND $N_{\text{initial}}$. Calculate gain $G_i$ as per Eq. 8 with $N_{\text{initial}}$ in the first stage and $N_{\text{orig}}$ as second stage.
7: if $G_i > G_{i-1}$ then $N_{\text{initial}} = N_i'$ // if gain improves then admit the new semantic $N_i$ ANDed with the existing first stage
8: elseif ($G_i < G_{i-1}$ && pairwise = TRUE) TERMINATE algorithm and return the existing first stage configuration $N_{\text{initial}}$ as output. // End the algorithm when there is no improvement in gain after exploring all combinations
9: end if
10: end if
11: end for // by the end of the for loop, the first stage $N_{\text{initial}}$ is either NULL or an ANDed configuration of all optimal semantic NNs. Next, we look at pairwise combinations of features that can be ORed in the first stage.
12: remove the semantic vectors already admitted into first stage $N_{\text{initial}}$ from the search space. # features in the remaining search space = $N'$, pairwise = TRUE. Select the top $k(k < N')$ features quality-wise from the $N'$ search space.
13: for $i = 1 : \binom{k}{2}$ // for each pair combination in the k-feature space
14: $N_{\text{initial}} = N_1$ OR $N_2$ // where $N_1$ and $N_2$ are the two NNs corresponding to the semantic pair for the $i^{th}$ combination
15: $N_{\text{temp}}' = N_{\text{initial}}$ AND $N_{\text{initial}}$
16: Obtain accuracy $Q'$ for the hierarchical framework with $N_{\text{temp}}'$ as first stage and $N_{\text{orig}}$ as second stage.
17: Repeat Steps 5-10 with $N_i$ = $N_{\text{temp}}'$ if quality constraint is met and gain obtained with current configuration is higher than previous configuration, then, $N_{\text{initial}} = N_{\text{temp}}'$
18: if $N_{\text{initial}}$ (current iteration) == $N_{\text{initial}}$ (previous iteration) then continue
19: else GOTO Step 12 and Repeat Steps 12-20
20: end for

as per Eq. 8 discussed earlier, are ANDed together and set as the initial stage ($N_{\text{initial}}$) (line 7). Next, we eliminate the semantic vectors already admitted into the initial stage and search through the remaining search space for pairwise ORed combinations of semantics from the top $k$ features that would improve the accuracy and the overall gain (lines 12-14). For datasets where inputs can be characterized by two different semantic features not shared among all the objects of interest

V. Design Methodology

In this section, we describe the procedure for training and testing the hierarchical framework.

A. Training the Hierarchical Framework

Algorithm 2 shows the pseudocode for training the hierarchical framework. The process is a continuation of the
Algorithm 2 Methodology to train the hierarchical framework
Input: Original classifier $N_{\text{orig}}$, training dataset $D_{\text{tr}}$ Output: Semantically decomposed hierarchical framework, $N_{\text{hier}}$ with optimised first stage  
1: Call Algorithm 1 on HSV space. initialize the output from Algorithm 1 as $N_{\text{color}} = N_{\text{initial}}$
2: Call Algorithm 1 on Gabor space. initialize $N_{\text{gabor}} = N_{\text{initial}}$
3: initialize $N_{\text{combo}} = N_{\text{color}} \text{ AND } N_{\text{gabor}}$
4: Calculate gain $G_{\text{color}}$, $G_{\text{gabor}}$, $G_{\text{combo}}$ as per Eq. 8 with each $N_i$ obtained from Steps 1-3 in the first stage and $N_{\text{orig}}$ as second stage.
5: Select the configuration corresponding to $\max(G_{\text{color}}, G_{\text{gabor}}, G_{\text{combo}})$ as $N_{\text{initial}}$
6: $N_{\text{hier}} = N_{\text{initial}}$ with maximum gain as first stage followed by $N_{\text{orig}}$ as second stage

Algorithm 3 Methodology to test the hierarchical framework
Input: Test instance $I_{\text{test}}$, hierarchical framework $N_{\text{hier}}$ with appropriate activation threshold
Output: $I_{\text{test}}$ classified as clutter or object of interest  
1: Obtain semantic feature vectors of $I_{\text{test}}$ which are passed as inputs to the NN(s) comprising the initial stage in $N_{\text{hier}}$
2: If output of the NN(s) in the initial stage of $N_{\text{hier}}$ is such that final classifier or second stage is not enabled, then TERMINATE testing and Output = $I_{\text{test}}$ classified as clutter.
3: If the initial stage NN(s) produce a sufficient confidence level on the output meeting the OR-AND conditions, then, second stage or final classifier is activated and Output = Output of final classifier. Please note that the input to the final classifier is the original test instance, $I_{\text{test}}$ and not the semantic feature vector.

| TABLE II | FIRST STAGE CONFIGURATION OF $N_{\text{hier}}$ FOR CALTECH101 |
|----------------|---------------------------------------------------------------|
| Image          | Configuration of first stage | Representations                      |
| Soccer Ball    | W:B                                                            | R:Red;W:White                        |
| Bonsai         | (Y+R)+G                                                        | B:Black;Y:Yellow                     |
| Lotus          | R+Y                                                            | G:Green                              |
| Sunflower      | Y                                                              |                                      |
| Stop sign      | R                                                              |                                      |
| Brain          | (G1+G2),G3                                                     | G1: (32$\sqrt{2}$,0$^\circ$); G2: (64$\sqrt{2}$,0$^\circ$) |
| Menorah        | G4+G5                                                          | G3: (32$\sqrt{2}$,0$^\circ$); G4: (32$\sqrt{2}$,90$^\circ$) |
| Revolver       | G6,G7                                                          | G5: (64$\sqrt{2}$,45$^\circ$); G6: (32$\sqrt{2}$,0$^\circ$) |
| Guitar         | G8+G9                                                          | G7: (64$\sqrt{2}$,45$^\circ$); G8: (16$\sqrt{2}$,0$^\circ$) |
| Starfish       | G10+G11                                                        | G9: (64$\sqrt{2}$,90$^\circ$); G10: (16$\sqrt{2}$,0$^\circ$) |
|                |                                                                | G11: (64$\sqrt{2}$,90$^\circ$) TEXTURE |

VI. EXPERIMENTAL METHODOLOGY
In this section, we describe our experimental setup used to evaluate the performance of the hierarchical framework. We have implemented an ANN based image recognition platform for the Caltech101 dataset [31] which is a large image dataset containing over 30,000 labeled examples of 101 different images. Each classifier used is a feedforward artificial neural network with 3 layers (Input, Hidden and Output). Each of the ANNs are trained using the standard backpropagation algorithm. For up to 50 different images of the dataset, we implemented the hierarchical framework ($N_{\text{hier}}$) trained to recognize the particular object of interest from a host of other images (clutter) exploiting both color and texture based semantic information. Of the 50 images, the initial stage configurations for 10 different images are shown in Table II. We can see that the first stage is set to different configurations of OR-AND (OR denoted as +, AND denoted as .) by the training methodology described in the previous section for both color and texture. Each of the Gabor filters selected are represented in the table by their corresponding (scale, orientation). The training methodology of the hierarchical framework confirms accuracy or quality check with that of the traditional classifier using OR operation and then it optimizes the efficiency using AND. The Gabor filters/colors selected in the process are also the most optimum semantics for the given set of images. In addition to Caltech101, we evaluated...
our approach on another dataset CIFAR10 [42] which consists of 60,000 colored images belonging to 10 classes. The initial stage configuration for 4 images are shown in Table III.

In this work, we used software simulations to obtain classification accuracy and hardware simulations to obtain energy values. We implemented the 2-stage semantically decomposed classification framework for the object detection application in Matlab. We measured runtime for the applications using performance counters on Intel Core i7 3.60 GHz processor with 16 GB RAM. For hardware implementation, we specified each classifier as an accelerator at the register-transfer logic (RTL) level [25]. We used the Synopsys Design Compiler to synthesize the integrated design to a 45nm SOI process from IBM. Finally, we used Synopsys Power compiler to estimate energy consumption of the synthesized netlists. We optimized the logic synthesis for energy using proper timing constraints to ensure that baseline is energy-efficient.

### VII. RESULTS

In this section, we present the experimental results that demonstrate the benefits of our approach. We use Caltech101 as our primary benchmark to evaluate the benefits with semantic decomposition.

#### A. Energy Improvement

Fig. 5 (a, b) shows the normalized improvement in efficiency with respect to the average single stage classifier (which forms the baseline) for the 14 images of Table II and III. We quantify efficiency as the average number of operations (or total number of MAC computations) per input (OPS). For each image in the dataset, we varied the fraction of clutter in the test set (60%, 75% and 90%) and evaluated the efficiency. As mentioned earlier, there is a significant disproportion in the distribution of input data [9]. Thus, in our experiments we evaluated our approach by varying the fraction of clutter (non-objects of interest) in the input data for an object detection task. We observe that the hierarchical framework provides between 1.97x-2.64x (average: 2.31x) improvement in average OPS/input compared to baseline across the 10 different images for Caltech. For CIFAR, the average reduction in OPS corresponds to 1.88x across the 4 different images. Note that the benefits vary depending on the fraction of clutter in the dataset. Fig. 5 clearly illustrates that maximum benefit for each image is observed when the fraction of clutter is 90%. This can be corroborated to the fact that the initial stage filters out a lot of the object of interest. In case of hardware implementation, the reduction in OPS for Caltech translates

#### B. Impact of Variation of Clutter on Efficiency

Here, we examine the impact of clutter on the overall efficiency of our proposed hierarchical framework. It is evident that the main idea behind semantic decomposition and building the hierarchical framework is to reject majority of clutter images in the initial stage. Being less complex than the final, the initial stage would contribute less to the overall

![Figure 5: Normalized OPS for images with (a) color as semantic (b) texture as semantic](image-url)

![Figure 6: Average hardware energy for different fraction of clutter in the dataset](image-url)

![Figure 7: Average hardware energy for different fraction of clutter in the dataset](image-url)
computational cost. So, the final stage should ideally get enabled only for the objects of interest and no clutter data at all. However, in practicality, the clutter data will have certain semantic information representative of the object of interest and will thus be passed to the next stage. Fig. 8 shows the fraction of clutter that is actually passed to the final stage as the clutter percentage is varied gradually from 60% to 90% for both CALTECH and CIFAR. We observe that as the clutter fraction is increased, the amount of clutter filtered out increases that correspond to lesser number of activation of the final stage. For instance, for 60% clutter images in the CIFAR10 dataset, the final stage is activated for 45.5% clutter, while for 90% clutter it is activated for 33.8%. Thus, we observe maximum savings in both energy and OPS as the fraction of clutter increases (Fig. 5, 6, 7).

C. Optimizing the complexity of the first stage

The hierarchical design methodology during training first meets the output quality or accuracy constraint and then optimizes the framework to get maximum efficiency. In order to get the most benefits, we need to filter out more clutter in the initial stage. We can achieve this by increasing the complexity of the first stage by adding more neurons to the hidden layer. Fig. 9 shows the normalized energy of the entire hierarchical framework as the complexity of the first stage is varied. It can be clearly seen that the amount of clutter filtered increases with the increasing complexity of the first stage. So, as the initial stage becomes more complex, the final stage is enabled for fewer clutter data from the total fraction of clutter. Thus, in the beginning, we observe a decreasing trend in energy. However, the increasing complexity of the first stage would also add an additional overhead to the cost computation that would at some point overcome the total cost savings. This break-even point corresponds to the maximum benefits or the lowest energy that we can achieve using the hierarchical framework for this particular example. Beyond this point, the cost increases. In Fig. 9, we see that the break-even point corresponds to 0.508 (Normalized energy) which translates to 1.97x improvement in computational cost. This behavior is taken into account in our design methodology described in the previous section.

D. Efficiency-Accuracy Tradeoff using Confidence level (δ)

In Section IV, we discussed that the final stage of the hierarchical framework is enabled if the activation module gets sufficient confidence level from the NNs in the first stage. Thus, we can regulate this confidence level or activation threshold (δ) to modulate the amount of clutter being passed to the final classifier and further optimize the efficiency. Fig. 10 shows the normalized energy of the hierarchical framework as the accuracy of the first stage is varied by changing the δ value. The analysis shown is with reference to images from Caltech101 dataset. Setting δ to a low value implies that more clutter will now be misclassified by the first stage, and forwarded to the final classifier. Increasing δ would result in lesser clutter being misclassified thus improving the overall accuracy of the first stage as can be seen from Fig. 10. Note that δ value can be increased until all objects of interest are correctly classified in the first stage and forwarded to the next. Beyond a particular δ, the objects of interest will be misclassified and filtered out. This δ value corresponds to the maximum overall accuracy of the first stage in the hierarchy. In Fig. 10, we observe that as the normalized accuracy value increases from 0.86 (δ=0.1) to 0.95 (δ=0.4), there is a 2.25x reduction in total # OPS which quantifies energy-efficiency. In this case, beyond δ=0.4 the accuracy declines and hence those δ values are not considered. Thus, the δ value serves as a powerful knob to modulate the efficiency-accuracy tradeoff which can be easily adjusted during runtime to get the most optimum results. Please note that the accuracies shown in Fig.
10 are normalized with respect to the baseline accuracy. The baseline accuracy in this case is 97.8

E. Combining Color and Texture in the Initial Stage

For a given dataset, the hierarchical training methodology first constructs the individual color/texture configurations. Then, the individual color/texture stages are ANDed together. In case, the overall gain of the hierarchical framework improves with the ANDed configuration, the color(AND)texture combination is selected as the first stage of the hierarchy. For certain images in the Caltech101 dataset shown in Table IV, such configuration was chosen. For all the images, the semantic selection methodology chose the corresponding colors and textures individually for initial stage construction. The training methodology, in addition to color ANDed the appropriate Gabor features in the initial stage. In order to observe the additional benefits with the ANDed configuration and for comparison purpose, we implemented a separate semantically decomposed framework using only color configuration obtained from Algorithm 1.

We conducted a similar set of experiments on the Caltech101 dataset by varying the fraction of clutter on the combined color/texture configuration. Fig. 11 shows the normalized #OPS for the images in Table IV (Representations are same as Table II). We observe that the framework provides 1.35x-1.79x improvement (with respect to the baseline) in average OPS per input as the clutter fraction is increased from 60% to 90%. Note maximum benefits correspond to larger clutter fraction in the dataset. It is evident that the benefits observed are due to conditional activation of the final stage. Now, in the combined configuration, the initial stage consists of AND operation. Hence, we can deduce that the final classifier in this case would get activated for lesser number of instances as compared to the configuration with only color as semantic. Fig. 12 shows the average energy in both cases (color, color AND texture) as the clutter fraction is varied. It is clearly seen that color AND texture configuration gives more savings than the latter. This is due to the fact that the benefits of reduced final stage activation in the combined case overcomes the penalty due to the addition of texture configuration in the first stage. Thus, our proposed design methodology ensures maximum cost savings by selecting the most optimum semantic configuration.

VIII. CONCLUSION

We presented a systematic approach to optimize energy-efficiency of machine learning classifiers by exploiting the characteristic semantic information of inputs. We observe that certain semantic information is common across various objects in a dataset. We use the common semantic features to distinguish the objects of interest from the remaining inputs in object detection applications. Based on the above insight, we proposed the concept of hierarchical classification based on semantic decomposition. We develop a systematic methodology to implement a 2-stage semantically decomposed classification framework using color/texture as semantic information. We achieve this by arranging the classifiers (ANNs) in increasing order of complexity as per the characteristic semantic features they are trained to recognise. The design methodology is equipped to implicitly gather the most appropriate semantic information for optimum efficiency. To quantify the potential of semantic decomposition, we used color and texture as a basis for segmentation and designed the hierarchical framework for object detection for various
images of the Caltech101/CIFAR10 dataset. Color and texture information were obtained using HSV and Gabor filtering operations, respectively. Our experiments demonstrate significant improvement in energy over hardware implementation with respect to traditional approach.

ACKNOWLEDGMENT

This work was supported in part by C-SPIN, one of the six centers of StarNet, a Semiconductor Research Corporation Program, sponsored by MARCO and DARPA, by the Semiconductor Research Corporation, the National Science Foundation, Intel Corporation and by the National Security Science and Engineering Faculty Fellowship.

REFERENCES

[1] Pradeep Dubey. Recognition, mining and synthesis moves computers to the era of era. 2005.
[2] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. 2014.
[3] Yuval Netzer, Tao Wang, Adam Coates, Alessandro Bissacco, Bo Wu, and Andrew Y Ng. Reading digits in natural images with unsupervised feature learning. In NIPS workshop on deep learning and unsupervised feature learning, volume 2011, page 4. Granada, Spain, 2011.
[4] Jeffrey Dean, Greg Corrado, Rajat Monga, Kai Chen, Matthieu Devin, Mark Mao, Andrew Senior, Paul Tucker, Ke Yang, Quoc V Le, and et al. Large scale distributed deep networks. In Advances in Neural Information Processing Systems, pages 1223–1231, 2012.
[5] Geoffrey Hinton, Li Deng, Dong Yu, Gevorge E Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N Sainath, et al. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. Signal Processing Magazine, IEEE, 29(6):82–97, 2012.
[6] Li Deng, Geoffrey Hinton, and Brian Kingsbury. New types of deep neural network learning for speech recognition and related applications: An overview. In Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on, pages 8599–8603. IEEE, 2013.
[7] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012.
[8] Swagath Venkataramani, Victor Bahl, Xian-Sheng Hua, Jie Liu, Jin Li, Matthew Philipose, Bodhi Priyantha, and Mohammed Shoab. Sapphire: an always-on context-aware computer vision system for portable devices. In Design, Automation & Test in Europe Conference & Exhibition (DATE), 2015, pages 1491–1496. IEEE, 2015.
[9] Ke Chen and Shihai Wang. Semi-supervised learning via regularized boosting working on multiple semi-supervised assumptions. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 33(1):129–143, Jan 2011.
[10] Jiang Wang, Zicheng Liu, Ying Wu, and Junsong Yuan. Learning actionlet ensemble for 3d human action recognition. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 36(5):914–927, May 2014.
[11] Antonio Feitosa Neto, Anne MP Canuto, et al. Meta-learning and multi-objective optimization to design ensemble of classifiers. In Intelligent Systems (BRACIS), 2014 Brazilian Conference on, pages 91–96. IEEE, 2014.
[12] Robert E Schapire. The boosting approach to machine learning: An overview. In Nonlinear estimation and classification, pages 149–171. Springer, 2003.
[13] Daniel Hernández-Lobato, Gonzalo Martínez-Muñoz, and Alberto Suárez. Empirical analysis and evaluation of approximate techniques for pruning regression bagging ensembles. Neurocomputing, 74(12):2250–2264, 2011.
[14] Li Deng and John C Platt. Ensemble deep learning for speech recognition. In INTERSPEECH, pages 1915–1919, 2014.
[15] Yi Sun, Xiaolong Wang, and Xiaou Tang. Deep convolutional network cascade for facial point detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3476–3483, 2013.

[16] Jan Hosang, Rodrigo Benenson, Piotr Dollár, and Bernt Schiele. What makes for effective detection proposals? 2015.
[17] João Gama and Pavel Brazdil. Cascade generalization. Machine Learning, 41(3):315–343, 2000.
[18] Paul Viola and Michael Jones. Rapid object detection using a boosted cascade of simple features. In Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on, volume 1, pages I–511. IEEE, 2001.
[19] Vincent Vanhoucke, Andrew Senior, and Mark Z Mao. Improving the speed of neural networks on cpus. In Proc. Deep Learning and Unsupervised Feature Learning NIPS Workshop, volume 1, 2011.
[20] Himanshu Kaul, Mark Anders, Sanu Mathew, Steven Hsu, Amit Agarwal, Farhana Sheikh, Ram Krishnamurthy, and Shekhar Borkar. A 1.45 ghz 52-to-162gops/w variable-precision floating-point fused multiply-add unit with certainty tracking in 32nm enos. In Solid-State Circuits Conference Digest of Technical Papers (ISSCC), 2012 IEEE International, pages 182–184. IEEE, 2012.
[21] Swagath Venkataramani, Anand Raghunathan, Jie Liu, and Mohammed Shoab. Scalable-efficient classifiers for energy-efficient machine learning. In Proceedings of the 52nd Annual Design Automation Conference, page 67. ACM, 2015.
[22] Vinay K Chippa, Harishankar Jayakumar, Debabrata Mohapatra, Kaushik Roy, and Anand Raghunathan. Energy-efficient recognition and mining processor using scalable effort design. In Custom Integrated Circuits Conference (CICC), 2013 IEEE pages 1–4. IEEE, 2013.
[23] Sungho Park, Ahmed Al Maasri, Yang Xiao, Kevin M Irick, and Vijaykrishnan Narayanan. Salienty-driven dynamic configuration of hmax for energy-efficient multi-object recognition. In VLSI (ISVLSI), 2013 IEEE Computer Society Annual Symposium on, pages 139–144. IEEE, 2013.
[24] Zidong Du, Avinash Lingamneni, Yunji Chen, Krishna Palem, Olivier Temam, and Chengyong Wu. Leveraging the error resilience of machine-learning applications for designing highly energy efficient accelerators. In Design Automation Conference (ASP-DAC), 2014 19th Asia and South Pacific, 2014.
[25] Swagath Venkataramani, Vinay K Chippa, Srimat T Chakradhar, Kaushik Roy, and Anand Raghunathan. Quality programmable vector processors for approximate computing. In Proceedings of the 46th Annual IEEE/ACM International Symposium on Microarchitecture, pages 1–12. ACM, 2013.
[26] Vinay K Chippa, Debabrata Mohapatra, Kaushik Roy, Srimat T Chakradhar, and Anand Raghunathan. Scalable effort hardware design. Very Large Scale Integration (VLSI) Systems, IEEE Transactions on, 22(9):2004–2016, 2014.
[27] Priyadarshini Panda, Abhronil Sengupta, and Kaushik Roy. Conditional deep learning for energy-efficient and enhanced pattern recognition. arXiv preprint arXiv:1509.08971 ACCEPTED for DATE 2016.
[28] Swagath Venkataramani, Ashish Ranjan, Kaushik Roy, and Anand Raghunathan. Axnn: energy-efficient neuromorphic systems using approximate computing. In Proceedings of the 2014 international symposium on Low power electronics and design, pages 27–32. ACM, 2014.
[29] Ludmila I Kuncheva. Combining pattern classifiers: methods and algorithms. John Wiley & Sons, 2004.
[30] Albert Hung-Ren Ko. Static and dynamic selection of ensemble of classifiers. PhD thesis, École de technologie supérieure, 2007.
[31] S. Avidan. Ensemble tracking. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 29(2):261–271, Feb 2007.
[32] Xu-Ying Liu, Jianxin Wu, and Zhi-Hua Zhou. Exploratory undersampling for class-imbalance learning. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 39(2):539–550, 2009.
[33] Haim Levkowitz and Gabor T. Herman. Glhs: A generalized lightness, hue, and saturation color model. CVGIP: Graphical Models and Image Processing, 55(4):271–285, 1993.
[34] Anil K. Jain, Nalini K. Ratha, and Sridhar Lakshmanan. Object detection using gabor filters. Pattern Recognition Letters, 322–325. IEEE, 2008.
[35] Tse-Wei Chen, Yi-Ling Chen, and Shao-Yi Chien. Fast image segmentation based on k-means clustering with histograms in hsv color space. In Multimedia Signal Processing, 2008 IEEE 10th Workshop on, pages 322–325. IEEE, 2008.
[36] Ma Li and Richard C Staunton. Optimum gabor filter design and local binary patterns for texture segmentation. Pattern Recognition Letters, 29(5):674–677, 2008.
[37] S Arivazhagan and L Ganesan. Texture classification using wavelet transform. Pattern recognition letters, 24(9):1513–1521, 2003.
[38] Mohammad Haghighat, Saman Zonouz, and Mohamed Abdel-Mottaleb. Identification using encrypted biometrics. In Computer Analysis of Images and Patterns, pages 440–448. Springer, 2013.

[39] Christoph Palm, Daniel Keysers, Thomas Lehmann, and Klaus Spitzer. Gabor filtering of complex hue/saturation images for color texture classification. In Int. Conf. on Computer Vision, volume 2, pages 45–49, 2000.

[40] Guang-Hua Hu. Optimal ring gabor filter design for texture defect detection using a simulated annealing algorithm. In Information Science, Electronics and Electrical Engineering (IIEEE), 2014 International Conference on, volume 2, pages 860–864. IEEE, 2014.

[41] Kevin Jarrett, Koray Kavukcuoglu, Marc Aurelio Ranzato, and Yann LeCun. What is the best multi-stage architecture for object recognition? In Computer Vision, 2009 IEEE 12th International Conference on, pages 2146–2153. IEEE, 2009.

[42] Alex Krizhevsky and G Hinton. Convolutional deep belief networks on cifar-10. Unpublished manuscript, 40, 2010.