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RESEARCH ARTICLE

Banknote recognition: investigating processing and cognition framework using competitive neural network

Oyebade K. Oyedotun[1] · Adnan Khashman[1,2]

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Abstract Humans are apt at recognizing patterns and discovering even abstract features which are sometimes embedded therein. Our ability to use the banknotes in circulation for business transactions lies in the effortlessness with which we can recognize the different banknote denominations after seeing them over a period of time. More significant is that we can usually recognize these banknote denominations irrespective of what parts of the banknotes are exposed to us visually. Furthermore, our recognition ability is largely unaffected even when these banknotes are partially occluded. In a similar analogy, the robustness of intelligent systems to perform the task of banknote recognition should not collapse under some minimum level of partial occlusion. Artificial neural networks are intelligent systems which from inception have taken many important cues related to structure and learning rules from the human nervous/cognition processing system. Likewise, it has been shown that advances in artificial neural network simulations can help us understand the human nervous/cognition system even furthermore. In this paper, we investigate three cognition hypothetical frameworks to vision-based recognition of banknote denominations using competitive neural networks. In order to make the task more challenging and stress-test the investigated hypotheses, we also consider the recognition of occluded banknotes. The implemented hypothetical systems are tasked to perform fast recognition of banknotes with up to 75 % occlusion. The investigated hypothetical systems are trained on Nigeria's Naira banknotes and several experiments are performed to demonstrate the findings presented within this work.

Keywords Banknote recognition · Competitive neural network · Neural processing · Cognition framework · Naira notes

Introduction

Neural networks are intelligent systems which can learn various tasks by adaptively updating its weights. Basically, neural networks are learning systems with motivations that are hinged on the biological nervous/cognition processing paradigms (Stafford 2010); they can be considered as simplified computational models which simulate the nervous/brain system in structure and function. These networks have found applications in many important areas where it is highly intricate, tedious or impossible to define mathematical relations associating input parameters with output parameters, neural networks can learn such complex and abstract functions mapping input parameters to output parameters in a phase known as training (Oyedotun and Khashman 2016). Trained neural networks are capable of making intelligent decisions on new cases with reasonable accuracies; this is termed as the generalization power of the neural network (Niyogi and Girosi 1996). The success of the field of neural networks is evident in the many emerging models of such networks nowadays. The structures and learning algorithms of the different networks are motivated by different scientific findings in the human nervous and cognition systems (Eluyode and Akomolafe 2013; Schuman and Birdwell 2013).

✉ Oyebade K. Oyedotun
oyebade.oyedotun@ecraa.com

Adnan Khashman
adnan.khashman@ecraa.com

[1] European Centre for Research and Academic Affairs (ECRAA), Mersin-10, Northern Cyprus, Lefkosa, Turkey

[2] University of Kyrenia, Mersin-10, Girne, Turkey

It is evident that advances in medical and psychology (cognition) findings largely influence the progress of neural network field. Generally, such important findings inspire new neural network structures and learning algorithms, or in the least, suggest significant modifications, which impact on learning experiences and therefore performances on various tasks. Although, many significant medical advances have been made over the years in the field of human vision, many critical questions relating to scene understanding based on hierarchical visual processing remain unequivocally unanswered by the research community (Amano et al. 2006; Diamant 2008). For example, the three schools-of-thought on hierarchical visual processing are the bottom-up, top-bottom and hybrid paradigms (McMains and Kastner 2011; Pinto et al. 2013; Graboi and Lisman 2013). In the bottom-up approach, hierarchical processing is conceived to be achieved through the sequential aggregation of primary scene features to more defined features and then finally to the object which is recognized (Itti et al. 1998). In contrast, the top-bottom conception of hierarchical visual processing suggests that an object for recognition is sequentially decomposed to component parts for analysis and then understanding (Oliva et al. 2003; Gilbert and Li 2013). In the hybrid approach, hierarchical visual processing is conceived as the combination of the bottom-up and top-bottom approaches; scene understanding or object recognition is achieved by employing both the bottom-up and top-bottom approaches in simultaneous parsing of the scene or object (Milanova et al. 2008). In order to be able to make significant advancements in answering some tough questions as discussed above, it is imperative that corresponding researches should not only address or investigate the biological but psychological/cognition conception of visual processing. Moreover, many researches support the idea that artificial neural networks can be leveraged on in the simulation of various hypothetical conceptions relating to nervous and cognition queries (Zhang et al. 2011; Long and Gupta 2008; Yamazaki and Igarashi 2013); this is reasonable since neural networks are artificial learning systems motivated by biological and psychological paradigms.

In this work, we investigate tough queries relating to the visual processing involved in banknote recognition. Although, the concept which motivated this work is much broader than the recognition of only banknotes, we found it sufficient to achieve the investigation of the considered hypotheses using full and partially occluded banknotes.

Business transactions are inevitable activities that we perform on a regular basis; we are either receiving or giving out money (banknotes). We rely on our ability to effortlessly recognize banknote denominations in order to perform these daily business activities smoothly. The human intelligence, visual processing ability and memory strength are strikingly awesome. Once we are accustomed to the different banknotes in circulation, the recognition of such banknote denominations somewhat becomes a trivial task; all we usually have to do for recognition is to have visual contact. Furthermore, although the task of recognizing partially occluded banknotes is somewhat more challenging, we are still able to achieve recognition with reasonable accuracies.

In an earlier work, the recognition of banknotes of two international currencies, Cyprus Pound and Turkish Lira was achieved using two different back propagation neural networks (Khashman and Sekeroglu 2004). Two separate back propagation networks were trained on processed images of the banknotes; one network was trained to recognize only Cyprus Pound banknote denominations and the other trained to recognize only Turkish Lira banknote denominations. A generalization recognition rate of 95 % was obtained in the work. In another related work, a single back propagation neural network was used to achieve the recognition of Cyprus Pound and Turkish Lira banknotes using a single neural network (Khashman and Sekeroglu 2005); the processed banknote images of both currencies were used to train a single neural network. Although, a drop in generalization performance was observed as compared to the work (mentioned above) in which two separate networks were implemented, the trained network achieved a recognition rate of 90 % on the test data. In another sequel work, the recognition of deformed Euros and Turkish Lira banknotes was achieved using a single back propagation neural network trained on regularly sampled (same regions are sampled in banknotes of the same currency and denomination) patches of the banknotes (Khashman et al. 2005). Biorthogonal Wavelet Transform (BWT) with 50 and 80 % compression ratios was used to simulate low and medium deformations respectively. Also, Discrete Cosine Transform (DCT) with 50 and 80 % compression ratios was used to simulate highly and extremely deformed banknotes respectively. An overall recognition rate of 98.07 % was obtained on the test data. It is important to note that in all of the earlier works briefly discussed above, the neural networks implemented for recognition were trained on the basis that both sides of a banknote denomination corresponds to one output class. i.e. target outputs were coded such that the target output is the same for either side of a banknote denomination supplied as input to the network. This is of course reasonable since the sides of banknotes should not affect its denomination or value; and the implementation approach for recognition is consistent with the human final understanding of banknote denominations. Nevertheless, one can review the process of banknote recognition based on the cognition behind recognition. In this paper, we use neural network to explore the following three basic queries relating to the visual processing on which banknotes recognition is achieved:

- Hypothesis 1: Is it that the side of a banknote is recognized in parallel with the denomination; and recognition is triggered by different neural activities? Also, does this hierarchical and more distributed processing framework aid recognition? Here, we advance the idea of multiplexing in biological neural systems, where sets of neural activities are treated as related expert systems.
- Hypothesis 2: Is it that a banknote denomination is recognized without any knowledge of the side presented; and that recognition is triggered by the same neuron for both sides of a banknote (front or back)? Also, does this processing framework aid recognition?
- Hypothesis 3: Is it that a banknote denomination and side are recognized simultaneously; and that recognition is triggered by different neurons? Also, does this recognition framework aid recognition?

Furthermore, the distinction of this work in comparison with the earlier works lies in that we aim not to only address the capability of neural network to recognize banknotes, but more importantly, the cognition framework behind the recognition of banknotes. Also, we have made the task much more challenging by stressing the recognition performance obtained on each of the three hypotheses using banknotes with up to 75 % occlusion. In addition, in contrast to all the earlier works which base the recognition of banknotes on back propagation neural network, we implement a more biologically inspired neural network, competitive neural network, as learning systems within this work. The different proposed hypothetical systems are trained and simulated on Naira banknotes, which is Nigeria's official currency.

The remaining sections in this paper are Sect. 2 which introduces the database used; Sect. 3 which describes the proposed hypothetical systems; Sect. 4 which introduces briefly competitive neural network; Sect. 5 presents the training of the hypothetical systems; Sect. 6 which presents simulation of trained hypothetical systems and results discussion; and Sect. 7 summarizes the idea investigated in this work and findings as conclusion.

Database and processing

The database used to achieve the investigation of the hypotheses addressed within this work is Naira banknotes, Nigeria's official currency. Since the main aim of this work is to investigate the cognition framework behind the recognition of banknotes, we use only 3 denominations of the Naira banknotes.

The banknote denominations used are 1000 Naira, 200 Naira and 50 Naira. Sample images showing the denominations are shown in Fig. 1. From Fig. 1, the Naira banknotes used are shown with both front and back sides of each denomination. 100 samples for each banknote denomination are collected for the purpose of training the 3 hypothetical systems discussed earlier; hence we have a total of 300 images as our database. i.e. 100 samples for 1000 Naira banknote, 100 samples for 200 Naira banknote and 100 samples for 50 Naira banknote. Furthermore, we collect 50 % occluded samples of the 3 different Naira banknote denominations mentioned above (1000 Naira, 200 Naira and 50 Naira). Figure 2 shows samples of the partially occluded banknotes. In order to further stress-test the hypotheses, we collect another (third) database with 75 % partial occlusion. Samples showing the banknotes are shown in Fig. 3. It will be seen that the samples described in the database have banknotes with 75 % occlusion or 25 % exposure for visual stimuli.

The motivation behind the database collection is to use the fully (100 %) exposed banknotes for training the hypothetical systems; this can be considered analogous to the period in which humans are learning the identification of banknotes. While, the idea behind occlusion is to reduce the area of banknotes exposed for visual stimulation in testing the hypotheses we aim to investigate; since humans are able to recognize banknotes of familiar a currency almost effortlessly after a period of using such banknotes. The original colour images used within this work are processed such that they are suitable to be fed as neural network inputs. Hence, the sequence below is used to obtain the final neural networks inputs.

1. Conversion to grayscale: The colour images are transformed to grayscale using the luminosity method described by Eq. 1.

$$f'(x,y) = 0.21R + 0.72G + 0.07B \tag{1}$$

   The Luminosity method of grayscale transformation takes into account the human visual appreciation of colours. The human visual processing system is most sensitive to green colour, then red colour and least to blue colour (Biswas 2011); hence, the corresponding weightings in Eq. 1.

2. Pattern averaging: This aims to reduce the dimensionality or size of the grayscale images. The reduction of the number of pixels reduces computational requirements, training time and generalization time. Pattern averaging is achieved using Eq. 2 (Khashman 2006).

$$PatAv_i = \frac{1}{s_k s_l} \sum_{l=1}^{S_l} \sum_{k=1}^{S_k} p_i(k,l) \tag{2}$$

   where i is the segment index; k and l are coordinates of segments in the x and y directions, respectively; S_k and S_l are the segments widths and heights, respectively;

Fig. 1 Front and back Naira banknote samples; *top row*: 1000 Naira banknote; *middle row*: 200 Naira banknote; *bottom row*: 50 banknote

Fig. 2 50 % partially occluded front and back Naira banknote samples; *top row*: 1000 Naira banknote; *middle row*: 200 Naira banknote; *bottom row*: 50 banknote

Fig. 3 75 % partially occluded front and back Naira banknote samples; *top row*: 1000 Naira banknote; *middle row*: 200 Naira banknote; *bottom row*: 50 Naira banknote

$p_i(k,l)$ is the pixel value at coordinate k and l in segment i; $PatAv_i$ is the average value of pattern in segment i presented to the i-th input neuron of neural network. The number of segments in each window on the banknotes and therefore input neurons is i, given in Eq. 3; where M*N is the size of input images.

$$i = \{0, 1, 2, 3 \ldots n\} \tag{3}$$

where n is obtained using Eq. 4.

$$n = \left(\frac{M}{s_k}\right) \cdot \left(\frac{N}{s_l}\right) \tag{4}$$

The segment size used within this work to obtain the average values representing the banknotes is $S_k = S_l = 16$; this results in n = 256, the total number of inputs to the neural network.

3. Normalization: The pixel values obtained from the pattern averaging technique described above are normalized to the range 0–1, which are now suitable as neural network inputs. Equation 5 is used to achieve normalization.

$$N.P = \frac{Pixel\,value}{Range\,of\,pixel\,values} \tag{5}$$

where N.P is the value of the normalized pixel.

Investigated hypotheses

This section addresses and expatiates on the 3 hypotheses introduced in Sect. 1. The hypotheses are translated into hypothetical systems which are later on simulated with neural networks. The scope of this work allows the investigation of the biological and cognitive concept of perception using banknotes. The understanding of the human visual processing is not an area that has been fully understood by scientists and experts (Müller and Krummenacher 2006; Navalpakkam and Itti 2006). It has been suggested that researches which aim to investigate both neural and cognitive processing should yield much more promising results and reveal more of the understanding of human visual processing than researches which singly investigate either (Amano et al. 2006). This work aims to investigate associative visual processing of visual stimuli using recognition of banknotes. However, the findings established within this work should be broader than the neural and cognitive understanding of only banknotes recognition. We found neural networks suitable for the investigation of the hypotheses addressed in this work for two reasons.

- Neural networks grossly simulate the biological nervous/brain processing system in structure and function (Hakimpoor et al. 2011; Arslan 2013). Hence, it is possible to examine or explore details of neural processing activities relating to visual stimuli using the banknotes described in Sect. 2. For example, only winner neurons weights are updated in competitive neural processing (Abdipoor et al. 2013). Likewise, winner neurons and specified topological neighbour neurons weights are updated in Kohonen learning or maps (Chaudhary et al. 2014; Hasan and Shamsuddin 2011). Hence, it is possible to deduce which neurons respond optimally to which patterns or stimuli.
- Neural networks are learning systems that also grossly agree with cognitive learning rules (Golosio et al. 2015). For example, performances on tasks get better with experience or training; this is quite consistent with learning in humans. Hence, cognition hypotheses can be implemented and tested as learning rules in neural networks. The cognition hypotheses which yield better performances at test time can be considered the most probably correct. For example, cognition will suggest that a learning system which achieves 0 % error on classifying training examples and 20 % classification error on testing examples is worse as compared to a learning system which achieves 10 % error on classifying training examples and 10 % on classifying testing samples. The first system is considered to have only memorized the training examples. This problem is addressed in artificial learning systems as over-fitting/regularization.

Hypothesis 1

This hypothesis suggests that the recognition of banknote denominations is achieved such that the side (front or back) of banknotes stimulates recognition in a set of neural activities; while the banknote denominations stimulates recognition in some other sets of neural activities. These related sets of neural activities are fired in some particular combinations and order to achieve the complete task of recognizing banknote denominations.

Figure 4 shows the translation of the hypothesis 1. In this case, recognition system 1a in Fig. 4 is the 'expert system' that aims to recognize what sides of banknotes the system is exposed to; while, recognition system 1b and system 1c in Fig. 4 compose 'expert systems' which aim to recognize the denominations of the banknotes (i.e. 1000, 200 or 50 Naira banknote). However, we can agree that the recognition of the particular sides of banknotes aids the recognition of the denominations; therefore the system1b and system 1c can be seen to exhibit some associative memory which is dependent on the first system; this is achieved in the way that the hypothetical system is connected. The corresponding biological analogy is such that some neural activities (translated as system 1a in Fig. 4) in the brain respond to visual stimuli by 'provoking' the

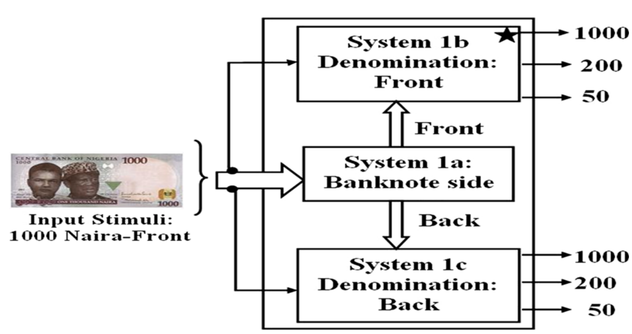

Fig. 4 Hypothetical system 1

recognition of the banknote sides (front or back); this information is processed in parallel with the banknote visual stimuli by other networks of neural activities aimed at determining the denominations. Either of system 1b or system 1c responds to input stimuli (banknote) based on the output of system 1a; system 1b responds/activates if system 1a outputs 'front', while system 1c responds if system 1 outputs 'back'. The output/signal of system 1a can be seen as the 'select' signal for system 1b and system 1c.

In plain artificial neural network concepts, system 1a is trained (as an expert system) to perform the recognition of the sides of banknotes as either 'front' or 'back' using both sides of banknotes collected from the database. System 1b is trained (as an expert system) to perform the recognition of banknote denominations using only the front sides of banknotes from collected database. System 1c is trained (as an expert system) to perform the recognition of banknote denominations using only the back sides of the banknotes from collected database. In Fig. 4, for example, the system is stimulated with 1000 Naira banknote 'front' side as input. System 1a neural system activates the 'front' select signal that 'excites' system 1b for the recognition of the banknote denomination; the black star shows the fired response. Conversely, system 1a 'inhibits' system 1c from responding to the recognition of the banknote denomination.

Hypothesis 2

This hypothesis suggests that the sides (front or back) and denominations of a banknote triggers or stimulates recognition simultaneously in neural processing activities/learning. The hypothesis assumes that the same set of neural activities stimulated by either side of a banknote fires the recognition of the denomination. i.e. the neural system directly fires the recognition of a banknote denomination irrespective of the banknote side that is supplied for visual stimulation.

Figure 5 shows hypothetical system 2. It will be seen that when the system is supplied the banknote, 1000 Naira-Top or 1000-Back, neural activities triggers recognition of the denomination as a 1000 Naira banknote; the fired recognition is show as black star. This approach has been used to achieve the identification of banknotes in many works (Khashman and Sekeroglu 2004; Khashman and Sekeroglu 2005; Khashman et al. 2005).

In plain artificial neural network concepts, the system is trained with both sides of the different banknotes such that the desired/target output is the same for any denomination irrespective of the sides presented. i.e. the desired/target output for 1000-Front and 1000-Back is the same; desired/target output for 200-Front and 200-Back is the same; and the desired/target output for 50-Front and 50-Back is the same. It therefore follows that there are 3 output neurons.

Hypothesis 3

This hypothesis suggests that the side and denomination of a banknote stimulates the response of different neurons in the neural activities responsible for learning; the sides of the banknotes contribute to the stimulation of different output neurons in recognizing the denomination. The hypothetical system is shown in Fig. 6. It can be seen that there are now 6 output neurons (3 pairs for the recognition of banknote denominations). For each pair, one of the neurons responds to the 'front' and the other responds to the 'back' side of the banknotes to achieve recognition. It will be seen that the back side of a 200 Naira banknote has been supplied to stimulate the system and the fired output neuron is marked with the black star. In this hypothesis, it is assumed that the sides of a banknote and denomination stimulate neural activities to which different neurons respond. In plain artificial neural network terms, the system is trained such that both sides of any denomination have different desired/target output.

Competitive neural network (CNN)

Competitive neural network (CNN) is based on the competitive feature found in biological neural activities (Castro et al. 2014). It is discovered that excitatory and inhibitory features are present in neural activities aimed at learning (Fukai and Tanaka 1997; Taylor and Alavi 1995). When biological neural systems are stimulated, neural activities 'provoke' excitations or inhibitions of neurons. The

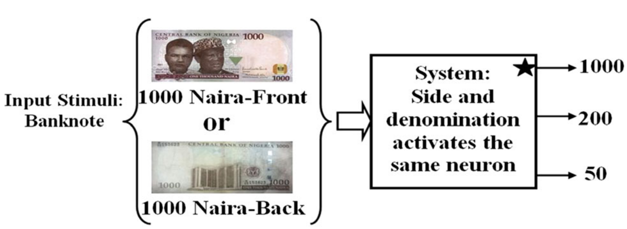

Fig. 5 Hypothetical system 2

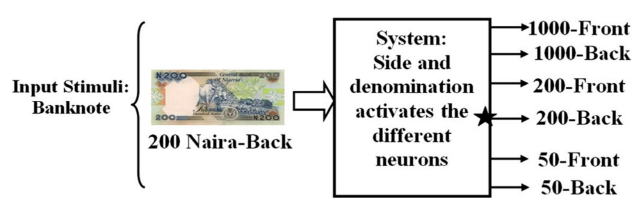

Fig. 6 Hypothetical system 2

synaptic weights of the neuron which responds optimally to the presented stimuli are updated; the neuron is referred to as the winner neuron. Conversely, all other neurons present in the neural system are referred to as loser neurons; and their synaptic weights are not updated for the presented stimuli. In many situations, different stimuli are applied to a neural system such that a number of different neurons respond to the different stimuli. In competitive learning, the same neuron responds to a particular or similar stimulus/pattern. Competitive neural network relies on the 'winner-takes-all' learning rule motivated by biological neural systems (Abas 2013); this learning rule is perhaps one of the milestones in unsupervised machine learning. Generally, competitive neural networks have two layers; the input layer (which is non-processing) where the input stimuli are supplied and the output layer where output neurons compete among themselves to become fired or activated. i.e. the winner-takes-all rule is applied in the output layer. Learning in competitive neural networks is achieved by moving the weight vector of a winner neuron towards to the corresponding input stimuli/pattern that triggers it. The total potential of all output neurons are computed each time the network is stimulated; the output neuron with largest total potential is the winner neuron. Figure 7 shows a typical competitive neural network. Note that interconnections among output neurons show excitatory and inhibitory connections which allows competition among output neurons based on the winner-takes-all learning rule. i.e. Fig. 7.

Equation 6 describes the computation of total potential, T.P, for output neurons.

$$T.P_k = \sum_{i=1}^{n} w_{ki} x_i \tag{6}$$

where $T.P_k$ is the total potential of output neuron k, x_i is input attribute with index i, n is the dimensionality of input pattern vectors, W_{ki} is the weight connection from input neuron i to output neuron k, and m is the number of output

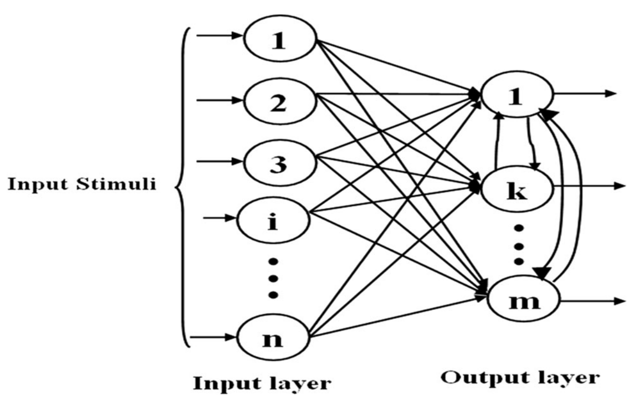

Fig. 7 Competitive neural network (CNN)

neurons corresponding to the number of expected distinct patterns or classes in the input data. Where, U_k is the output of neuron k, and j indexes the other neurons in the output layer.

$$\begin{aligned} &u_k = 1, \quad \text{if } T.P_k > T.P_j \quad \text{for all } j, k \neq j \\ &\text{else} \\ &u_k = 0 \end{aligned} \tag{7}$$

The constraint put on the weight update of the winner neuron is described in Eq. 8. Where, W_k is the weight matrix for output neuron, k; n is the dimensionality of the input vector. The weights update rule for a winner neuron, k, is described in Eq. 9 and 10 (Haykin 1998). Where, x is input and p is the index for training epochs.

$$W_k = \sum_{i=1}^{n} w_{ki} = 1 \tag{8}$$

$$\Delta w_{ki} = \eta (x_i - w_{ki}) \tag{9}$$

$$w_{ki}^{(p+1)} = w_{ki}^{(p)} + \Delta w_{ki} \tag{10}$$

Although, it is possible to use some other models of neural networks to achieve the investigation of the discussed hypotheses; we found competitive neural network suitable since it implements an unsupervised learning scheme and allows the network itself to discover the patterns of the used banknotes. Competitive neural network is a more biologically inspired and plausible neural network model, which allows more realistic simulations of biological neural activities on which the different cognition frameworks are based. Moreover, it is shown in some works that biological neural systems do not back propagate errors as obtains in back propagation neural networks (Ahissar and Hochstein 2004; Behrmann et al. 2004). Instead, in biological neural systems, neurons outputs are only forward propagated (Ahissar and Hochstein 2004; Behrmann et al. 2004); and learning is achieved in somewhat an unsupervised fashion. In contrast, implementing a supervised learning scheme in which networks are 'guided' on which output neurons should fire for the different input stimuli (banknotes) makes it less suitable to achieving the queries of our investigation; implementing such a learning scheme makes the recognition task less challenging.

Training of hypothetical systems

This section presents the implementation and training of the 3 hypothetical systems described in Sect. 3. The hypothetical systems are trained with 100 samples of each banknote denomination. The distribution of the banknote database is described in Table 1. In Sect. 2, the pattern averaging technique used to rescale the banknote images to

Table 1 Banknotes database distribution

Banknote	Side	Number of samples
50 Naira	Front	50
50 Naira	Back	50
50 Naira—Total	Both	100
200 Naira	Front	50
200 Naira	Back	50
200 Naira—Total	Both	100
1000 Naira	Front	50
1000 Naira	Back	50
1000 Naira—Total	Both	100
Naira banknotes—Total		300

a size of 16 × 16 pixels (256 pixels) as described. Hence, it follows that all network trainings and simulations within this work are carried out using 16 × 16 pixels grayscale images of the considered banknote denominations.

Hypothetical system 1

In Sect. 3, the detailed description of hypothetical system 1 is given under hypothesis 1. It will be seen that the hypothesis is described as composing 3 related neural systems which are system 1a, system 1b and system 1c. For the sole sake of convenience and clarity, combined systems system1a, system 1b and system 1c will be henceforth referred to as 'hyp1'. System 1a, which performs the recognition of the sides of banknotes, is translated to the competitive neural network, CNN1a, shown in Fig. 8. The system is a competitive network with 256 input neurons (the number of input image pixels: 16 × 16) and 2 output neurons. The output neurons are meant to compete to be fired for either side of the presented banknotes; 1 of the output neurons should win for all presented 'front' sides of the different banknotes denominations, while the other output neuron should fire (win) for all presented 'back' sides of the different banknote denominations. From Table 1, it will be seen that the distribution of banknote sides is a total of 150 banknotes for 'front' (50 front samples each for 50, 200 and 1000 Naira) and 150 banknotes for 'back' (50 back samples each for 50, 200 and 1000 Naira).

Furthermore, system 1b is translated to competitive neural network, CNN1b. System 1b is trained to recognize the different banknote denominations using only the front sides of the banknotes. System 1b is described in Fig. 9.

It will be seen in Fig. 9 that there are 3 output neurons; where the 3 output neurons compete to become winner for the 3 different banknote denominations, based on the presented front sides of 50 Naira, 200 Naira, 1000 Naira banknotes. The front side of a 50 Naira banknote is used to exemplify this in Fig. 9; with the front side a 50 Naira banknote supplied as input, it is assumed that neuron 1 wins. Also, it is assumed that neuron 2 and neuron 3 win for the front sides of 200 and 1000 Naira banknotes, respectively.

Lastly, system 1c is translated to competitive neural network, CNN1c, shown in Fig. 10. Also, it will be seen that the network has 3 output neurons.

The system is trained to perform the recognition of the different banknote denominations using only the 'back' sides of the banknotes. The back side of a 200 Naira banknote has been used to exemplify this in Fig. 10; with the back side of a 200 Naira banknote supplied as input, it is assumed that neuron 2 wins. Also, it is assumed that neuron 1 and 3 win for the back sides of 50 and 1000 Naira banknotes, respectively. It will be seen that the coupling of hypothetical system 1 is such that system 1b and system 1c relies on the output of system1a (front or back side of supplied banknote) in order to activate either system 1b or system 1c; hence, system 1a can be considered a 'nervous multiplexer', selecting neural activities to achieve final recognition of the banknote denominations.

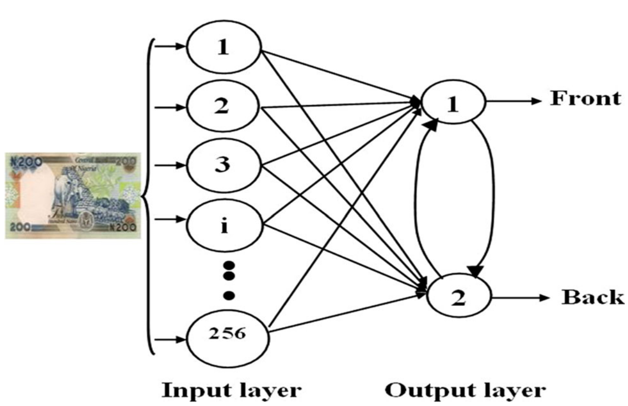

Fig. 8 Hypothetical system 1: CNN1a

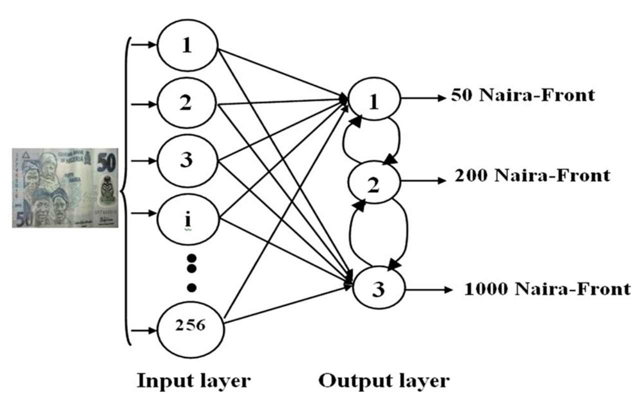

Fig. 9 Hypothetical system 1: CNN1b

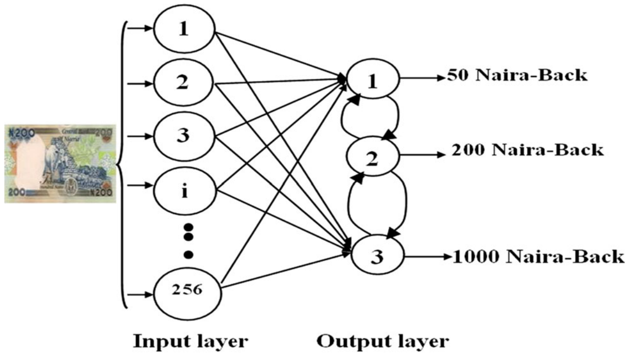

Fig. 10 Hypothetical system 1: CNN1c

Table 2 describes the training parameters for the hypothetical system 1, composed of 3 systems, CNN1a, CNN1b and CNN1c.

Table 2 shows important network parameters such as learning rate, conscience factor, epochs and training time. It will be seen that the networks achieved learning in a time range of 25–30 s; this fast training is attributed to the unsupervised learning scheme on which competitive learning is based. Also, it will be noted there are no achieved errors for the networks in Table 2, since there are no target outputs in unsupervised based learning systems. This contrasts with supervised learning schemes (based on the back propagation algorithm) in which error gradients computations are carried out in the output layer and propagated back into the network for weights update.

Hypothetical system 2

This hypothesis suggests that the same neuron is fired for both sides (front or back) of a banknote denomination. Figure 11 shows the translation of the system as a competitive neural network, CNN2. It will be seen that there are 3 output neurons which compete among themselves to become fired; each of the output neurons wins for either side of the 3 different banknote denominations. For example, in Fig. 11, the network is supplied/stimulated with the front side of a 1000 Naira banknote and it is expected that output neuron 3 wins; it should be noted that the same output neuron 3 wins for the back side of 1000 Naira banknotes. Likewise, output 1 wins for either side of 50 Naira banknotes; and output 2 wins for either side of 200 Naira banknotes.

Please, note that not all competitive interconnections in the output neurons are shown in the competitive networks. The training parameters for hypothetical system 2 are shown in Table 3. For sake of compactness, hypothetical system 2 is referred to as 'hyp2'; it will be seen that learning is achieved in 100 epoch, taking 26 s.

Table 2 Training parameters for hypothetical system 1: hyp1

Parameter	CNN1	CNN2	CNN3
Number of input neurons	256	256	256
Number of output neurons	2	3	3
Learning rate (η)	0.47	0.47	0.47
Conscience factor (k)	0.00001	0.00001	0.00001
Epochs	100	200	200
Training time (s)	30	25	31

Hypothetical system 3

Hypothesis 3 suggests that neural activities fire different neurons in response to either sides of a banknote. Hypothetical system 3 is translated to a competitive neural network, CNN3, in Fig. 12. Please, note that not all competitive interconnections are shown for the output neurons.

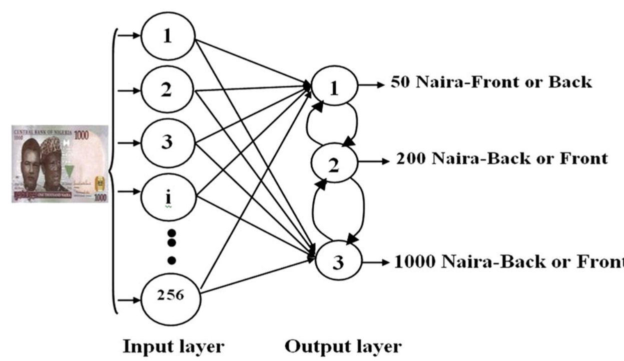

Fig. 11 Hypothetical system 2: CNN2

Table 3 Training parameters for hypothetical system 1: hyp2

Parameter	CNN4
Number of input neurons	256
Number of output neurons	3
Learning rate (η)	0.47
Conscience factor (k)	0.00001
Epochs	100
Training time (s)	26

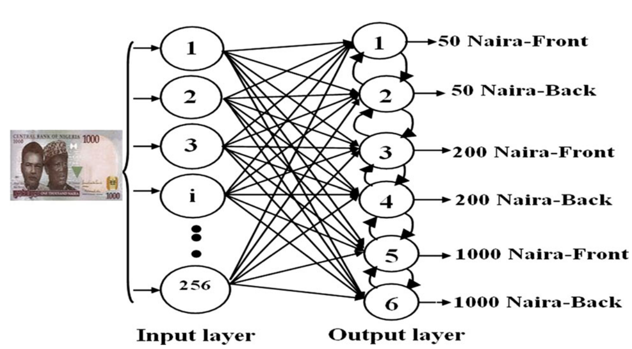

Fig. 12 Hypothetical system 3: CNN3

In Fig. 12, for example, the network is supplied/stimulated with the front side of a 1000 Naira banknote and is it assumed that output neuron 5 is fired or wins.

Furthermore, it is assumed that output neuron 6 is fired for the back side of a 1000 Naira banknote. It is seen that different neurons compete to become fired or winner for either sides of any banknote denomination. Hence, the network has 6 output neurons in the output layer, where they respond in pairs to either sides of the banknote denominations. Also, hypothetical system 3 is referred to as 'hyp3' for compactness. Table 4 describes the training parameters for hyp3. It will be seen that hyp3 achieved learning in 100 epochs, taking 28 s.

Testing of systems and results discussion

This section presents the testing of 3 hypothetical systems described in the previous sections. The trained hypothetical systems, hyp1, hyp2 and hyp3 are simulated with training data, and test data. It is to be noted that the samples contained in the test data are not contained in the training data; this allows the observation of the generalization power of the hypothetical systems. The distribution of the simulation data is given in Table 5. The testing data are similar but not the same samples of banknotes contained in the training data; hence, the testing data are fully exposed (with 0 % occlusion) banknotes just has obtains in the training data.

Conversely, the two other different databases are collected with 50 and 75 % occluded banknotes spanning both front and back sides as shown in Table 5. The databases with occlusion are aimed at stress-testing the considered hypotheses and making the recognition task more challenging. Samples of banknotes with 50 and 75 % occlusion can be seen in Sect. 2, under Figs. 2 and 3, respectively. The hypotheses are tested on achieved recognition rates for the 3 different banknotes, 50 Naira, 200 Naira and 1000 Naira. The recognition rates of the systems are obtained using Eq. 11; where R.R is the recognition rate.

$$R.R = \frac{Number\ of\ correctly\ classified\ samples}{Number\ of\ test\ samples} \quad (11)$$

From Table 6, it will be seen that the lowest recognition rates are achieved on the training and testing data based on hypothesis 2 (hypothetical system 2); 50 % recognition rates were achieved. This can be explained in that the hypothesis does not support the system in firing the same output neuron for both sides of a banknote denomination. It can be conceived that both sides of a banknote do not fire the same neuron during learning; the output neurons are capable of responding to only a side of the banknote, hence, the lower recognition rates achieved on the

Table 4 Training parameters for hypothetical system 1: hyp3

Parameter	CNN5
Number of input neurons	256
Number of output neurons	6
Learning rate (η)	0.47
Conscience factor (k)	0.00001
Epochs	100
Training time (s)	28

Table 6 Recognition rates (R.R) for hypothetical systems

Parameter (samples)	HYP1	HYP2	HYP3
Training data (300)	99.33 %	50 %	99.33 %
Testing data (120)	100 %	50 %	100 %
50 % Occlusion data (60)	56.67 %	43.33 %	46.67 %
75 % Occlusion data (60)	26.67 %	23.33 %	26.67 %
Overall recognition rate (540)	86.67 %	46.30 %	85.56 %
Total runtime (s)	0.052	0.012	0.023

Table 5 Testing banknotes database distribution

Banknote	Side	Testing data	50 % occlusion	75 % occlusion
50 Naira	Front	20	10	10
50 Naira	Back	20	10	10
50 Naira—Total	Both	40	20	20
200 Naira	Front	20	10	10
200 Naira	Back	20	10	10
200 Naira—Total	Both	40	20	20
1000 Naira	Front	20	10	10
1000 Naira	Back	20	10	10
1000 Naira—Total	Both	40	20	20
Naira banknotes—Total		120	60	60

A dual core intel (R) (2.00 GHz) CPU with 3 GB RAM is used for all trainings and simulations

hypothesis. Also, this problem is observed on 50 and 75 % occluded testing banknotes, resulting in an overall recognition rate of 46.30 %. However, the hypothetical system requires a total runtime of 0.012 s.

Hypothesis 3 comes second in performance, achieving an overall recognition rate of 85.56 %. The hypothesis supports the idea that both sides of the banknotes stimulate different output neurons for learning. Recognition rates of 99.33 and 100 % are achieved on the training and testing data, respectively. Also, it is observed that a slightly higher runtime of 0.023 s is required to simulate all test samples.

The highest overall recognition rate, 86.67 %, is achieved on hypothesis 1, which supports the idea that neural activities are parallel and hierarchical; some neural activities select which other neural activities should be triggered or excited towards achieving a particular task. The hypothetical system requires as a runtime of 0.052 s.

Hence, it is conceived that neural activities exhibit multiplexing features, where the subsequent triggered neural activities are selected by the outputs of previous neural activities. This nature of distributed and hierarchical neural firing or processing in human vision and perception has been suggested in many researches (Axelrod and Yovel 2012). Furthermore, in recent times, it is observed that the most successful neural network models in machine learning which are referred to as deep learning networks are based on hierarchical and distributed stimuli processing (Han and Li 2015; Zhang et al. 2015). Alternatively, hypothesis 1 can be conceived of as suggesting that the nervous system is composed of numerous interconnected neural systems which are in themselves somewhat miniature and dependent expert systems, relying on excitation or inhibition signals from other interconnecting miniature neural expert systems. Generally, many of these miniature neural expert systems are excited in some specific order and combination to achieve a particular task; this is somewhat plausible, since, the brain contains billions of interconnected neurons (Herculano-Houzel 2009). Furthermore, it will be seen in Table 6 that hypothesis 1 outperforms hypothesis 2 and 3 on achieved recognition rate using 50 % occluded banknotes; the multiplexing feature exhibited by neural system 1 in hypothetical system 1, allows the other two dependent systems, system 1b and system 1c, to focus on the recognition of banknote denominations using only the front and back sides of banknotes, respectively. It is conceived that hypothesis 1 exhibits a more elaborate distributed information processing; 3 different set of neural activities are required to perform the complete recognition of banknote denominations. This contrasts with the hypotheses 2 and 3, which implements only a set of neural activity to achieve recognition.

Also, hypothesis 1 supports the idea of associative memory, where, the recall of the banknote sides (front or back) aids and simplifies the task of recognizing the banknote denominations. Similarly, humans more often than not achieve objects recognition or scene understanding through associative memory (Voss 2009; De Rover et al. 2008); we often recall or recognize unfamiliar faces by first recalling where we met them. Such interconnected (associative) memory schemes have been shown to be very helpful and important to humans (Chaumon et al. 2008).

Another important point is that hypothesis 1 and 3 seem to be achieving the same goal. It will be noted that the final outputs in hypothesis 1 and 3 achieve the recognition of both the banknote denominations and sides, though the actual interest is only in the denominations. This concept is somewhat consistent with humans, where is it impossible to say we recognize banknotes without the knowledge of which side we are presented with, even when we have no recognition interest in the banknote sides. It is conceived that such associative memory and cognition framework aids the recognition of banknote denominations. This is demonstrated in the achieved recognition rates obtained in hypotheses 1 and 3. Conversely, hypothesis 2 totally excludes the identification of banknote sides; it achieves solely the recognition of banknote denominations. This is somewhat inconsistent with human memory on the task of recognizing banknote denominations; hence, the obtained low recognition rates on hypothesis 2, where the least performance on recognition is observed.

Furthermore, from Table 6, it will be seen that hypothetical system 1, hyp1, has the highest run (simulation) time of 0.052 s as compared to hypothetical system 2 (hyp2) and hypothetical system 3 (hyp3) with run times of 0.012 and 0.023 s, respectively. We posit that the relatively long processing time observed in biological neural systems can be seen as somewhat analogous to the fact that hypothesis 1 required the highest runtime, where more distributed and hierarchical excitation or inhibition of neurons in some specific order result in long propagation of information signals and therefore processing time.

Conclusion

Humans reserve an advanced, robust and sophisticated visual processing system. We are able to almost effortlessly recognize, and then use banknotes after a period of seeing them. Furthermore, our visual system is so graceful and efficient such that banknotes can be recognized even under some level of partial occlusion. Conversely, machines or artificial visual processing systems strive to achieve human performance on visual perception. Moreover, it is suggested that advances in the understanding of the human

visual processing system and cognition frameworks should result in better modeling of artificial systems in machine vision.

In this work, we investigate 3 hypotheses on the processing and cognition framework behind the recognition of banknotes using artificial neural networks. In contrast to some earlier works which solely concern themselves with the recognition of banknotes using back propagation neural networks, we investigate 3 hypothetical cognition frameworks behind banknotes recognition based on biological and psychological (cognition) foundations. Although, it is possible to use some other models of neural networks to achieve the investigation of the discussed hypotheses; we find competitive neural network suitable to investigate the hypotheses, since it relies on an unsupervised learning scheme and allows the network itself to discover the patterns of the used banknotes. Furthermore, competitive learning allows a closer simulation of biological neural activities which we seek to investigate within this work; we aim to explore neural activities triggering the recognition of banknote denominations. Hence, we conceive competitive neural network to be more biologically natural and plausible in observing neural activities. Also, implementing an unsupervised learning scheme makes the recognition task more challenging.

In the first hypothesis, we advance the idea of biological nervous multiplexing, where the sides of banknotes (front or back) is processed in parallel with the denomination by 3 different set of neural expert systems. However, the neural system which recognizes the sides of presented banknotes selects which of the other two neural systems is triggered for the final recognition of the banknote denomination. The second hypothesis suggests that the recognition of banknote denominations is achieved without any knowledge of the presented banknote sides (front or back). A single neural system (or set of neural activities) can achieve the complete recognition of banknote denominations. In this hypothesis, the same neuron is stimulated for either sides of a particular banknote denomination. In the third hypothesis, recognition of banknote denominations is achieved such that different neurons respond to either sides of a particular banknote denomination. Also, it is assumed that a single neural system achieves the complete recognition of banknotes. The considered hypotheses are translated into hypothetical systems and investigated using artificial neural networks.

In order to achieve the queries of this research, Naira banknotes, the official currency of Nigeria, have been used as database. Neural networks (hypothetical systems) are trained and simulated on the database. Furthermore, occluded banknotes are used to simulate the hypothetical systems; this allows the stress-testing of the hypothetical frameworks even further. The simulation results based on overall recognition rates show that highest performance is obtained in hypothesis 1 (86.67 %); hypothesis 3 slightly lags hypothesis 1 in performance (85.56 %); while a poor performance is obtained in hypothesis 2 (46.30 %). The obtained results support hypotheses 1 and 3 in view of the visual processing and cognition framework behind the recognition of banknote denominations; while hypothesis 2 looks far less plausible biologically.

It is noteworthy that the motivation behind this work is much more than the recognition of only banknotes; we investigate critical queries on the structure of the human visual processing system and plausible neural activities which ‘provoke’ different cognition frameworks. It is the hope that more researches which concurrently address neural activities and cognition frameworks would produce more significant findings than researches which address either singly.

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