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SILECT: System of Interactive Education for Learning and Earning using Computer Technology

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SILECT: System of Interactive Education for Learning and Earning using Computer Technology

(A Research-in-Progress)

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Abstract

System of Interactive Education for Learning and Earning using Computer Technology (SILECT) is an effective yet simplistic Information Communication and Technology (ICT) system that is proposed with the clear intention to teach numerals to marginalized group of people of developing world. The project develops on further based on four major underlying concepts namely learning by teaching theories; operant conditioning theories; neural network theories; people and participation concepts; and last but not the least Trainees as Trainers Model (TasT). After learning numerals as a preliminary phase, which supports the earning phase, trainees are capable of teaching others using the SILECT tool.

Keywords:

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1 Background

Nepal, with a population of 30 million and a per capita income of about $750, is passing through a momentous and prolonged political transition following a 10-year violent conflict that ended in 2006 [1]. Nepal's HDI is 0.458, which gives the country a rank of 157 out of 187 countries with comparable data [2]. Nepal's economic growth continues to be adversely affected by the political uncertainty. Nevertheless, real GDP growth is estimated to increase up to almost 5 percent for 2011/2012. This is a considerable improvement from the 3.5 percent GDP growth in 2010/2011 and would be the second-highest growth rate in the country's post-conflict era. Sources of growth include agriculture, construction, financial, and other services. However, ICT for development can be a catalyst for bringing in economic prosperity by creating employment opportunities for marginalized communities, where the practice of effective implementation of technology is still rudimentary.

It is universally understood that the requirement of formal education for gaining employment is considered compulsory. However; as with most of the developing nations of the world, the literacy rate of Nepal also needs to undergo a dramatic improvement in order to establish the country's population as a competitive work force in the international arena. With education index at 0.356, it's a high time to prioritize education in Nepal. Having much of the country's population living in rural and remote areas, increasing the ease of access towards secondary education (grades 9-12) remains a major challenge, as evidenced by the disturbingly low net enrollment rate of about 24 percent at this level. More than half of primary level students (grades 1-5) do not enter secondary schools (grades 6-10), and only one-half of them complete secondary schooling. In addition, fewer female students than male students join secondary schools and, among those who do join, fewer complete the 10th grade [1]. As a result, the number of students with incomplete/insufficient level of formal education accumulates over the year, clearly unable to enter the national work force. This situation clearly emphasizes the importance of a new mechanism for teaching and training to fulfill the demands of learners. That methodology should be interactive and creative enough to attract more and more students from all parts of the country with diverse economic profiles, prioritizing rural communities, to join hands in making slogan "education for all" as realistic goal. Utilizing technology as the tool for development, an effective solution can be realized with deeply transforming potential.

One of such application of technology with far reaching potential is making people literate. The ability of recognizing and writing characters and numerals opens many ways for learners, including adult learners, towards self paced development. There have been various researches to explore the plausible alternatives for interactive learning based on computer technologies; namely research on improving UI for Handwriting Based Learning Number by Saad, Razak, et. al. for pre-school children working in English scripts [3]. The UI for Handwriting Recognition Systems in Devnagari scripts is the topic that is implemented to meet the objectives of the project. Learning by teaching using Operant Conditioning Theories for enthusiastic learning, the core underlying concepts of deploying UI using the artificial neural network theories, people and participation focused programs are the major building blocks upon which the paper is conceptualized.

The rest of the paper is organized as follows. Section 2 presents research problem, followed by objectives of the study in Section 3. Importance of the study is highlighted in Section 4 and scope of the study in Section 5. Multidisciplinary literature review is detailed in Section 6.

Section 7 speaks of research methodology used in the paper. Section 8 explains the proposed solution. Section 9 explains the data collection and analysis. Section 10 highlights results and conclusions. The last section concludes with the further discussions.

2   Research Problem

What is an education methodology that can be effective enough to raise interests in learning and generate employment opportunities as an enhancement in developing countries using ICT?

3   Objectives of the Study

To devise a basic non formal learning methodology for human empowerment in developing countries via ICT based on Trainees as Trainers Model (TasT).

4   Importance of the Study

In comparison to conventional teaching methods using blackboard and chalk, modern educational systems with interactive and self-contained practices are favorable for providing lucrative offers for rural community people of developing regions. Every small or large project

requires some cross checking for success or failure and as a part of this activity; the study based on TasT model itself produces learners or trainers out of novice trainees which is itself a success indicator.

5   Scope of the Study

The target group is the marginalized people of the developing countries who are deprived of basic education in a timely fashion and thus suffering from high unemployment. The study includes figuring out the distinct system features for meeting the objectives defined within the context of developing countries. So the basic hindrances would be gaining confidence from the trainees themselves to participate. In other words, limitations might exist as different communities have their own set of requirements and to make a common point for meeting the target would be challenging.

6   Literature Review

Literature Review section comprises of detail explanation on how the authors have come up to the research question and how it was resolved based on the past theories, research works and publications from various disciplines.

6.1   Some key concepts

Beginning with some basic definitions of key terminologies that would be discussed in the paper as being addressed in PhD Dissertation of C. Chapagain [7]:

6.1.1   Human capital:

Human capital is the acquired knowledge and skills that an individual brings to an activity. Forms of human capital also differ among themselves. A college education is a different type of human capital than the skills of a cabinetmaker acquired through apprenticeship training. Human capital is formed consciously through education and training and unconsciously through experience.

(Elinor Ostrom in Social Capital by P. Dasgupta. & I. Serageldin, 2000:175)

6.1.2   Capacity

Capacity is an ability to perform, deliver, maintain and strengthen any work, project or program. "It is a living / open system. An organization with capacity is alive. It is flexible and vibrates with life, and cheers. It responds to changes and seeks out opportunities for innovation."(CRWRC, 1997: 43). It nourishes and flourishes with incentives and stimulus.

e.g. She has an enormous capacity for hard work.

His capacity for learning languages astonished me.

A fuel tank with a capacity of 50 liters.

(These limited resources are restricting our capacity for developing new products examples have been drawn from The Oxford Advanced Learner's Dictionary).

6.1.3 Capability

The quality of being capable. It refers to how well or how efficiently one accomplishes his/her task/responsibility.

6.1.4 Building

Though it is often used to indicate a relatively permanent, essentially box like construction having a roof and often windows, such as a house or school that has a roof and walls, but here it refers to the process and effort of developing something particularly human attributes/qualities like skills, efficiency, potentialities etc.

6.1.5 Capacity building

Capacity building is an approach to develop one's own potentiality in order to enhance his/her performance or output. It is not a separate entity but is in fact an integral part of overall HRM/HRD program. It is a response to the multi-dimensional (organizational, intellectual, social, political, cultural, physical, practical, financial) processes of change; not a pre-packaged interventions to bring intended outcome.

Capacity building must always be context-specific. Its effectiveness and sustainability rests on it being firmly rooted in the socio-cultural context of an organization's contextualized vision of the future, not on distant or detached generic ideals.

6.2   Education and Economic Empowerment

New research proves the long held expectation that human capital formation (a population's education and health status) plays a significant role in a country's economic development. Better education leads not only to higher individual income but is also a necessary (although not always sufficient) precondition for long-term economic growth. [9]

Evidence shows beyond any reasonable doubt that, at the individual level, more years of schooling generally lead to higher income. But, at the macroeconomic level, empirical evidence relating changes in education measures to economic growth has so far been ambiguous. Many authors suggest that this may be due to problems with the global empirical data on human capital (Barro and Lee 1996; de la Fuente and Doménech 2006; Cohen and Soto 2007; Benhabib and Spiegel 1994; Pritchett 2001). In a new major study recently published in Science, Lutz et al. (2008) provide for the first time the unambiguous statistical evidence (based on econometric models) that education is a consistently significant determinant of a country's aggregate level of economic growth. Last but not least, the analysis illustrates that the fruits of investments in education need a long time to ripen, to translate the education of children into better human capital of the adult labor force. The fruits will come slowly but surely. While education is not always a sufficient condition to growth, it can be considered a necessary one, at least in the longer run. Education is a long-term investment associated with near-term costs, but in the longer run it is one of the best investments a society can make for its future (Lutz et al. 2008).

Starting from the work of Mankiw, Romer and Weil (1992) and Barro (1991), there has developed a large literature -Hanushek (1995), Temple (2001), Krueger and Lindahl (2001), Gemmel (1996), Benhabib and Spiegel (1992) – on the positive association between education quantity and economic growth. Education quantity is measured by schooling enrolment ratios (Mankiw, Romer and Weil 1992, Barro 1991, Levine and Renelt 1992), the average years of schooling (Hanushek and Woessmann 2007, Krueger and Lindhal 2001), adult literacy rate (Durlauf and Johnson 1995, Romer 1990), education spending (Baladacci et al.). However, there are studies that find a weak association between education quantity and growth -Bils and Klenow (2000); and Prichett (2001) finds no relation at all between schooling and economic growth. The relationship between schooling quality and economic growth is examined in the work of Barro (1999), Hanushek and Kimko (2000), Hanushek and Kim (1995), Hanushek and Woessmann

(2007). The studies of Hanushek and Kimko, Hanushek and Kim and Hanushek and Woessmann develop a measure of labor force quality based on cognitive skills in mathematics and science and find that this has a strong and robust influence on economic growth. Barro (1999) based upon the data on student scores on internationally comparable examinations to measure schooling quality finds a positive relation between schooling quality and economic growth. On the empirical front, the focus of the studies on education quality has been on test scores.

As being addressed in the concluding remarks by the author of the paper entitled "The Role of Education in Economic Growth"-

"These countries should increase government expenditure on education with a view to increasing education quality. Education policy that focuses on the provision of facilities aimed at improving the number of trained teachers, survival rates, reducing pupil-teacher ratios, schooling life expectancy and performance levels based on test scores will promote economic growth. In conclusion, it can be argued that the interaction effect of government expenditure on education quality is significant for economic growth [9]".

Directly strengthening humans and their capabilities and health is likely to be a very effective strategy for improving human wellbeing in the longer run. [10]

The author further continues in his paper addressing that he would analyze by going from the bottom up; i.e. by starting with people because they are the agents of development and their wellbeing is the criterion and ultimate objective of any development. But people not only matter through the changing size of their population or its age structure and regional distribution, but rather by what they do for their own wellbeing and that of others. This depends in the first instance on their capabilities and skills. The best technologies are of no use without the people to operate them.

6.3 People and Participation

The shortages of high skill workers experienced in different economic sectors of developing countries are the outcomes of weaknesses in the whole education edifice, which commonly include: low participation and completion rates; prohibitive private and social costs associated

with senior high school and higher education; curriculum gaps at school and in higher education [11].

Cernea (1985) remarks that "Putting people first in development projects is not just about organizing people but it means empowering them to be social actors rather than passive subjects and take control over the activities that affect their lives." The sense of empowering inclusion that comes from content creation is valuable. But the first priority for the poor is typically employment, which opens many possibilities. Use of mobile telephones is widespread. To date, the poor have created incomes both *around* the technology—such as selling accessories and prepay cards—and *via* the technology—by selling or taking phone calls [12]. The sixth lesson published by InfoDev from an analysis of 17 of their pilot programs has also emphasized employment as:

Lesson 6: Projects that focus on ICT training should include a job placement component.

These two illustrations and many others clearly urge that today's human development is directly proportional to not only the ordinary training but also participatory actions bringing out positive vibes and self confidence among trainees. The second and rather vital result after a successful training and learning program is creation of employments as well especially in developing countries.

6.4   Learning by teaching

Definition of "Learning by teaching" as mentioned in [13]:

"In professional education, **learning by teaching** (German: *Lernen durch Lehren*; *LdL*) designates currently the method created by Jean-Pol Martin that allows pupils and students to prepare themselves to teach lessons, or parts of lessons. Learning by teaching should not be confused with presentations or lectures by students, as students not only convey certain content, but also have the flexibility to convey the content as they choose or develop their own methods and didactic approaches in teaching classmates the material. Neither should it be confused with tutoring, because the teacher has intensive control of, and gives support for, the learning process in learning by teaching as against other methods.

Students as teachers in order to improve the learning-process: Learning becomes more effective when students could engage in active tasks. The first attempts using the learning by teaching method in order to improve learning were started at the end of the 19th century."

Additionally [14] broadens the idea as "What's the best way to motivate listless, uninterested students? Simply turn them into teachers! The technique practiced at several schools and universities, most notably at St. John's College in Annapolis, Maryland, and at more and more grammar schools in Germany is called Learning by Teaching and requires a radical shift in the traditional roles of teacher-learner. The results are overwhelmingly positive, especially in the field of foreign language instruction. Learning by teaching is not an exclusively modern didactic method. Seneca wrote 2000 years ago, docendo discimus: "We learn by teaching." At St. John's College, students teach each other philosophy and physics, ancient Greek and the integral calculus by using the "Great Books," the original works of Euclid, Shakespeare, Newton, and Freud. There are no textbooks and no professors; the "tutors," as they are modestly called, see themselves as guides who know what questions to ask and, more importantly, know when to listen. St. John's students are not extraordinarily brilliant, but they are extremely motivated and critical. By the end of the first semester at the latest, they realize that they themselves are responsible for the quality of the seminars and tutorials."

According to a presentation given at the ASTA 2006 National Conference in Kansas City by Richard Culatta and Monte Belknap (Brigham Young University) entitled "Summary of students media use", three key merits of media use by students are : Highly interactive, highly integrated, and highly interesting. Besides knowing these illustration on how learning while teaching can be interesting enough using ICT tools, let's go back to the learning theories themselves. [15]

There are three main categories into which learning theories fall:

1. Behaviorist Theories 2. Cognitive Theories 3 .Constructivist Theories

In this paper, we are conceptualizing ideas based on Behaviorist theory [16], specifically the behaviorism i.e. operant conditioning, which involves the use of reinforcement to encourage behaviors.

Operant conditioning is an important concept in psychology. Operant conditioning is a learning process that involves an increase or decrease in the likelihood of some behavior as a result of the

consequences. There are four types of learning processes in operant conditioning: positive reinforcement, negative reinforcement, positive punishment, and negative punishment. [16]

Definitions and Types of Operant Conditioning

Positive Reinforcement: Positive reinforcement occurs when the likelihood of a certain behavior increases as a result of the presentation of something pleasant after the behavior.
Negative Reinforcement: Negative reinforcement occurs when the likelihood of a certain behavior increases as the result of removing something unpleasant after the behavior.
Positive Punishment: Positive punishment occurs when the likelihood of a certain behavior decreases as the result of the presentation of something unpleasant after the behavior.
Negative Punishment: Negative punishment occurs when the likelihood of a certain behavior decreases as the result of the removal of something pleasant after the behavior.

Operant Conditioning Examples

Examples of Positive Reinforcement: We may continue to go to work each day because we receive a paycheck on a weekly or monthly basis.   If we receive awards for writing short stories, we may be more likely to increase the frequency of writing short stories. Receiving praise for our karaoke performances can increase how often we sing. These are all examples of positive reinforcement.

Example of Negative Reinforcement: Imagine that you decided to open a window in your home. However, you are not happy with the noise from the traffic. Thus, you decide to turn on the radio and listen to music. This makes the traffic noise less noticeable. The frequency in which you turn on the radio when the window is open has increased. This would be an example of negative reinforcement. Turning on the radio has resulted in a decrease in the unpleasantness of the traffic noise.

Example of Positive Punishment: An example of positive punishment is when the negative behavior of an employee decreases as the result of being criticized by a supervisor.

Example of Negative Punishment: An example of negative punishment is when the frequency in which an employee is late for work deceases as a result of losing the right to listen to music while he or she works.

Negative Reinforcement vs. Punishment

It is important to not confuse negative reinforcement and punishment. They are different. Negative reinforcement involves an **increase** in a behavior. In contrast, punishment involves a **decrease** in a behavior.

How the operant conditioning is implemented in the study would be explained at the later part of this paper in the Proposed Solution.

Next part of literature review deals with the core concepts used in the implementing SILECT Handwriting Recognition System in Devnagari scripts which are theories and algorithms related to artificial neural networks.

6.5   Neural Networks

Examples of using tools or machine to assist in performing human resource intensive as well as repetitive tasks can be found out throughout the history of human evolution. With the progress of time, the tools of hunters and gatherers evolved into the tools of industrial civilization. Rapid development in electronics resulted in the modern day tool, i.e. computers. These machines are solution to the issues faced by humans which needed to be addressed at least more than once in their life time. Coffee machines, printers, cars etc are a few concrete physical examples solving such issues. Software solutions have even more impact as it enables essential services of modern society - stock market, banking, e-commerce, interactive learning, etc. Human mind is one of the most amazing machines which have progressively made all these tools since the beginning of the civilization.

The human brain consists of numerous cells called neurons arranged in a network. Each neuron communicates with many other neurons via exchange of signals called synapses. Each neuron performs functions which collectively give rise to memory, thoughts, processing, etc that happens in a human mind. Some neurons work as computational unit gathering inputs from other neurons and deciding whether it should produce synapse. Other neurons forms memory unit gathering and storing information received previously. Research shows that the majority of area of brain consists of similarly structured network. Experiments [17] have shown that auditory cortex in mice, the area of brain responsible for hearing, can be re-wired to receive optic signal

and be re-trained to perform visual recognition tasks. This gave rise to "one learning algorithm" and experiments were performed to see whether one part of brain, pre-trained for a specific task, can be re-trained to perform tasks usually performed by different part of the brain with similar structure. Feeding electrical representation of images recorded by camera into the tongue, the tactile sensor processing area of brain can learn to "see" [19]. A functional "third eye" was successfully implanted on a frog [S2.4]. These experiments show that regardless of the simplicity of the unit's basic structure, i.e. a neuron cell and its connections, collective network of vast number of neurons present in the brain makes it one of the most adaptive powerful computational machines outperforming any computer.

Researchers have explored the mechanisms of biological neural networks applicable in machine learning of similar tasks (ex. autonomous vehicle driving [20], visual object identification, speech to text, etc). Development of artificial neural network for carrying out tasks that human mind seamlessly performs is an example of such efforts. For any neural network, training the network i.e., the process of learning the parameters of the network which govern what function the network carries out, makes the most computationally intensive step. Introduction of "backpropagation" algorithm reduced some computational load for training a simple neural network and thus initiated wide spread interest in the research field. Significant improvement in the processing capacity of modern processors and introduction of high performance graphic processors and have shown major advances in handwritten digit recognition.

Various authors have published their research work on English digit classification. A list of performance of different algorithms with their test set error from a standard database (MNIST) of handwritten English digits [21] has been maintained by Yan LeCun. The database contains 60,000 training examples and 10,000 test set images. The network developed by Geoffrey E. Hinton has obtained an error rate of 1.53%. Although networks with better accuracy, the best with error rate of only 0.23% [22], has been reported, the mechanics of neural network and training algorithm taught by Hinton [23] and Andrew Ng [24] was used to implement core logic of digit recognition software required for this paper. The online course uses considerably smaller neural networks and thus suits the need of this paper and offers simple and computationally inexpensive operations required to deploy low-cost solution for interactive learning.

6.5.1 Neural Network Theory

The biological neural network can be modeled as graph where each node represents a neuron and each edge between two nodes represent connection between the nodes [S6, S7]. A simple model of the structure of a biological neural network with few nodes and related edges can be modeled as presented in Figure 1 below:
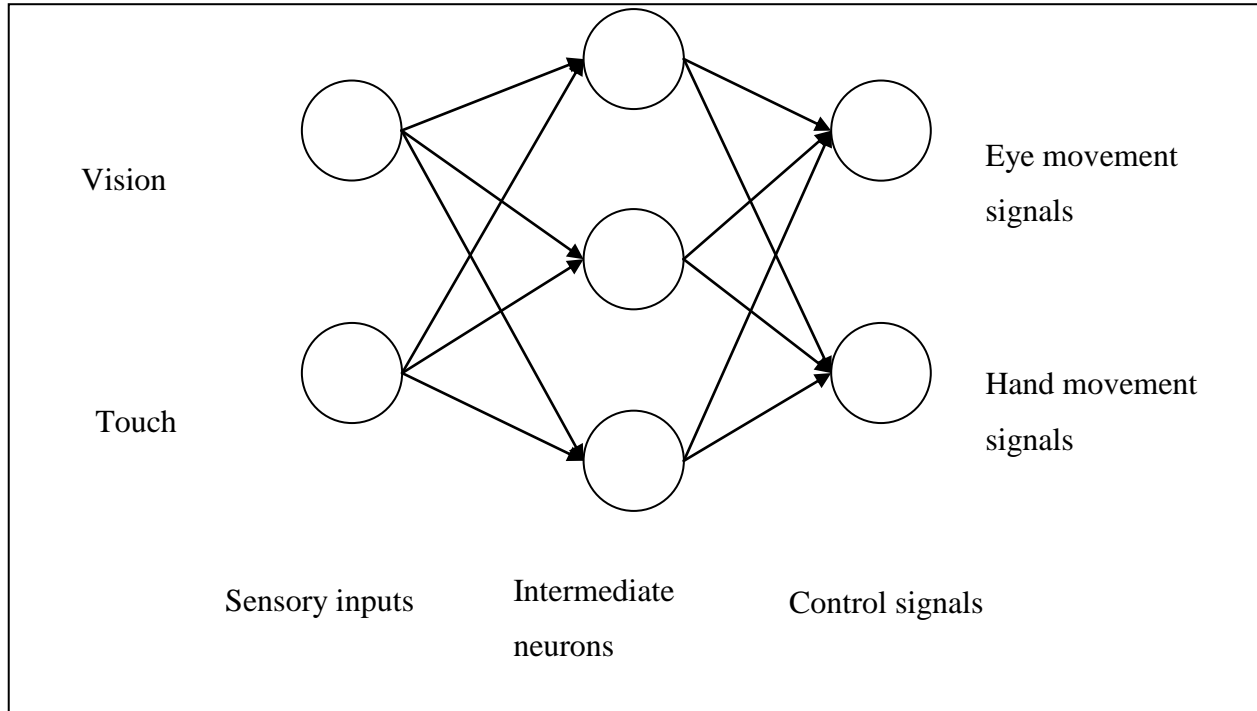

Figure 1 - Structure of a simplistic biological neural network

Artificial neural networks, or referred simply as neural network share the same structural elements as biological neural networks. The number units in input layer and output layer are dependent on the tasks that the neural network is designed to solve. The intermediate layer is referred to as hidden layer and there can be more than one hidden layer. A simple neural network with no interconnection among units of same layer is modeled as a k-partite graph.
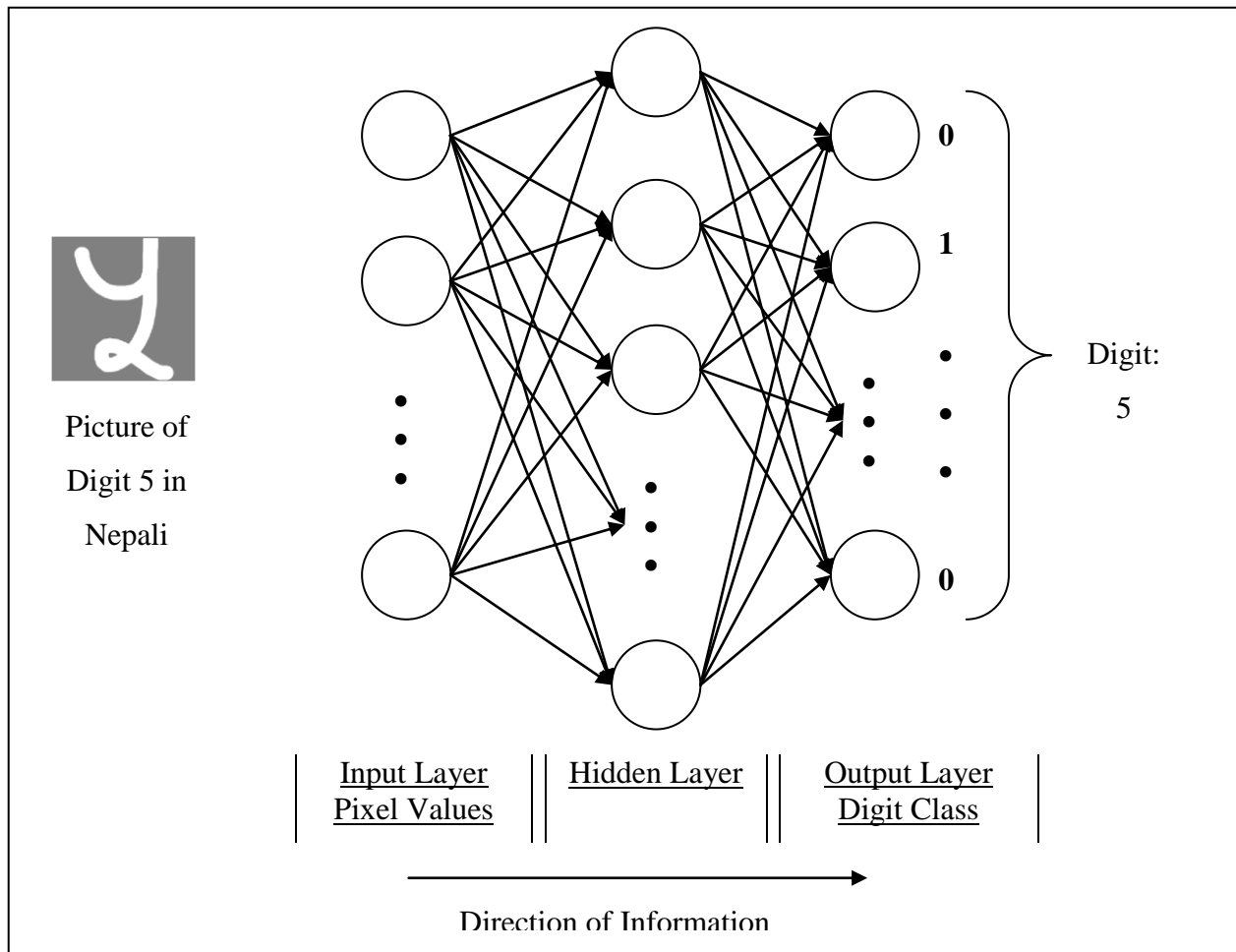
Figure 2 - Structure of an artificial neural network for digit recognition

As shown in Figure 2 above, each node or unit in the input layer receives values from outside the network. Each edge connecting two nodes has a value assigned to it which is used to scale the value of the input unit. Values propagate from input to output via successive hidden layers. Each unit in a layer sums its weighted inputs and performs necessary computation before passing it into the next layer.

A neural network, showing its remarkable similarity to a biological network, performing visual recognition is shown in Figure 2 below:
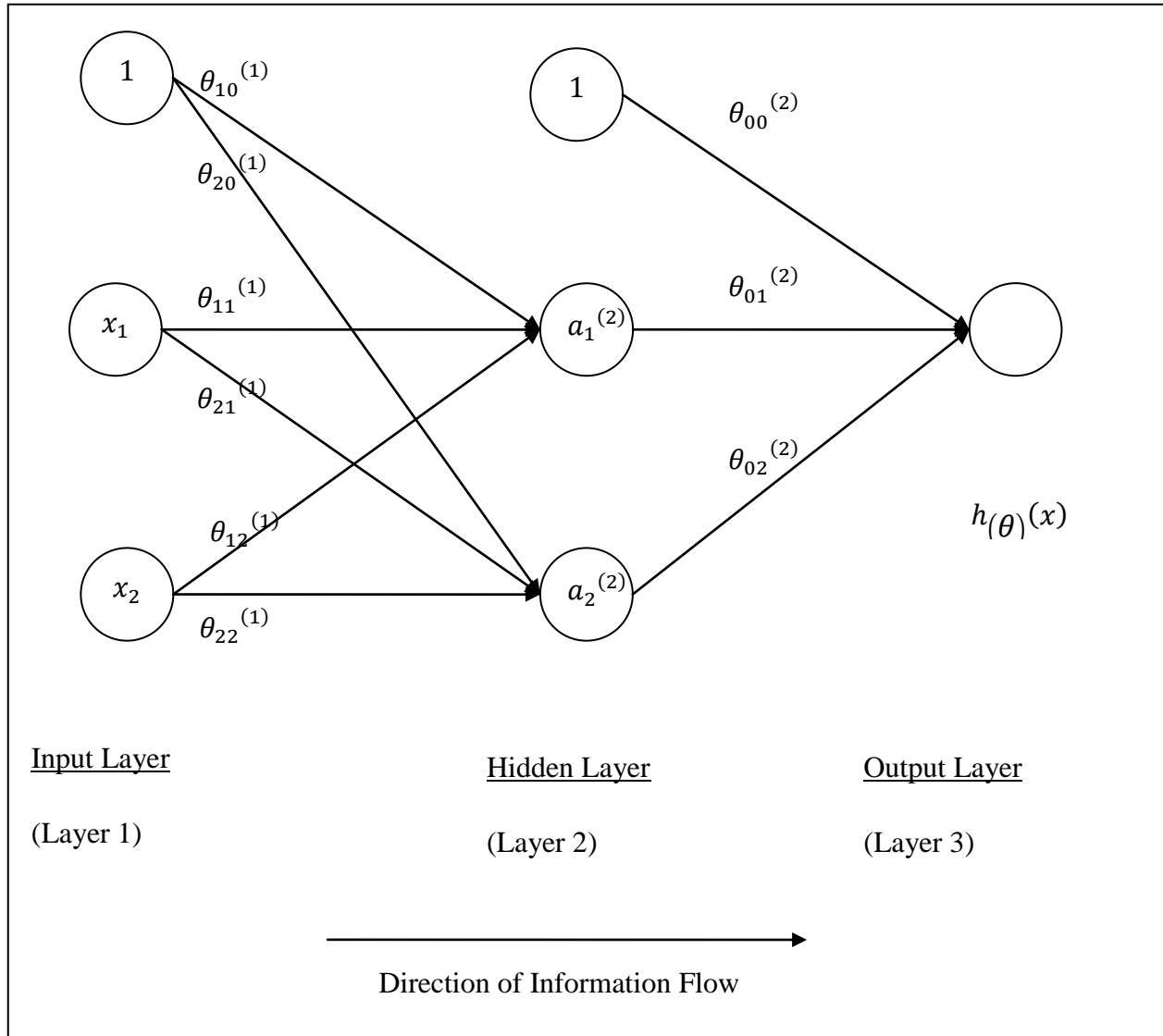
Figure 3 - Propagation of information in a logistic neural network

The neural network shown in Figure 3 has three layers. The state or value of each node is computed from previous layer's input and the weight on edges connecting the two layers. In a typical feed-forward logistic neural network, information flow to the unit on the next layer identified by head of arrow of the directed edges. In a logistic neural network, state of each node is computed as sigmoid function of the sum of weighted inputs. The sigmoid function or logistic function is defined as

$$\sigma(z) = \frac{1}{(1 + e^{-z})}$$

Calculations [S6, S7]:

Layer 1: Input units

Input vector x is of the form

$$\begin{bmatrix} 1 \\ x_1 \\ x_2 \end{bmatrix}$$

Parameter matrix $\boldsymbol{\theta}^{(1)}$ is of the form

$$\begin{bmatrix} \theta_{10}^{(1)} & \theta_{11}^{(1)} & \theta_{12}^{(1)} \\ \theta_{20}^{(1)} & \theta_{21}^{(1)} & \theta_{22}^{(1)} \end{bmatrix}$$

Parameter matrix $\boldsymbol{\theta}^{(2)}$ is of the form

$$\begin{bmatrix} \theta_{10}^{(2)} & \theta_{11}^{(2)} & \theta_{12}^{(2)} \end{bmatrix}$$

Layer 2 - Hidden units

Sum of weighted inputs $\boldsymbol{z}^{(2)}$ is computed as

$$\boldsymbol{z}^{(2)} = \boldsymbol{\theta}^{(1)} \times \boldsymbol{x}$$

$$= \begin{bmatrix} \theta_{10}^{(1)} & \theta_{11}^{(1)} & \theta_{12}^{(1)} \\ \theta_{20}^{(1)} & \theta_{21}^{(1)} & \theta_{22}^{(1)} \end{bmatrix} \times \begin{bmatrix} 1 \\ x_1 \\ x_2 \end{bmatrix}$$

$$= \begin{bmatrix} \theta_{10}^{(1)} + \theta_{11}^{(1)} \times x_1 + \theta_{12}^{(1)} \times x_2 \\ \theta_{20}^{(1)} + \theta_{21}^{(1)} \times x_1 + \theta_{22}^{(1)} \times x_2 \end{bmatrix}$$

State of units $\boldsymbol{a}^{(2)}$ is computed using sigmoid or logistic function

$$\boldsymbol{a}^{(2)} = \sigma\big(\boldsymbol{z}^{(2)}\big)$$

Layer 3: Output units

Sum of weighted inputs $\mathbf{z}^{(3)}$ is computed as

$$\mathbf{z}^{(3)} = \boldsymbol{\theta}^{(2)} \times \boldsymbol{a}^{(2)}$$

$$= \left[\theta_{10}^{(2)} + \theta_{11}^{(2)} \times a_1 + \theta_{12}^{(2)} \times a_2 \right]$$

Output of the network $\boldsymbol{h}_{(\boldsymbol{\theta})}$ is computed as

$$\boldsymbol{h}_{(\boldsymbol{\theta})} = \sigma\!\left(\mathbf{z}^{(3)}\right)$$

Due to the nature of logistic function used, the value of the output unit always stays within [0, 1] inclusive. The output value of logistic neural network is interpreted as probability of classification. For multi-class classification used for digit recognition, there are as many units in output layer as there are number of distinct class labels. Index of the unit in output layer with maximum value is selected as predicted digit.

Cost or Error function $J(\theta)$: [24]

The error function used is a cross-entropy error function for logistic neural network. Error of classification with respect to network parameters θ is averaged over all training examples. For multi class classification with K labels, computed as average error over all m training examples. Output $h_{(\theta)} \in \mathbb{R}^K$ where $\left(h_{(\theta)}(x^{(i)})\right)_k$ indicates state of kth unit in output layer. For single class classification, K is just 1.

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} \sum_{k=1}^{K} \left[-y_k^{(i)} \log\left(\left(h_{(\theta)}(x^{(i)})\right)_k\right) - \left(1 - y_k^{(i)}\right) \log\left(1 - \left(h_{(\theta)}(x^{(i)})\right)_k\right) \right]$$

Neural Network Training:

The goal of training a neural network is obtaining the set of parameters θ that minimizes the overall error function. A naive method of iterating over all values in the parameter space and selecting the parameters which gives lowest error is theoretically possible. However, as the number of parameters grow linearly, the combinations of parameters grow exponentially making iterating over all possible set of parameter values practically infeasible. Training of neural network is performed using gradient descent algorithm. The algorithm uses partial derivatives calculated using backpropagation algorithm.

Backpropagation: Obtaining the appropriate weight parameter θ that minimizes the cost function is an important process and a very computationally intensive one if one is to perform exhaustive search across weight space. Thus the method presented in [S6, S7] minimizes error function by finding partial derivatives (gradients) required for performing gradient descent algorithm. Partial derivatives of the error function with respect to each weight are evaluated for calculating how much a the weight is contributing to the error. The gradient descent algorithm simply follows the path directed by gradients towards minimum slope in an iterative loop set to run a finite number of times or until further iterations produce no more significant reduction in error value.

From the above discussion, we can see that the study has raised certain genuine questions and also some promising research areas for bringing in better learning methodologies for empowering human capital of developing countries.

7   Research Methodology

The study is a quasi-experimental research working with two sets of groups of people; one trained by teaching numerals using SILECT system and another not trained at all. The procedure of training model, data collection, analysis and results are mentioned in the paragraphs below.

8   Proposed Solution

The proposed solution of SILECT system comprises of three major parts – Input, Process and Output as being depicted in Figure 4 below:
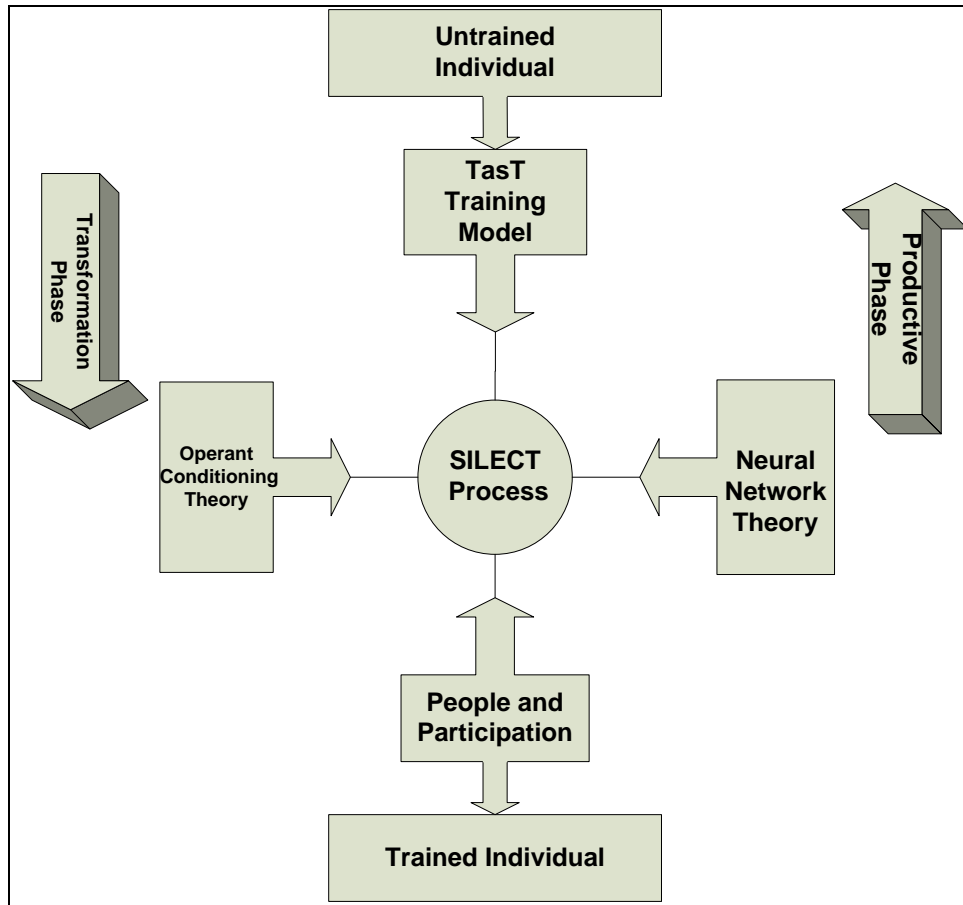
Figure 4 - Proposed Solution

Input parameters are the beneficiaries of the project i.e. the untrained individuals who want to learn Devnagari digits. Process comprises of sub parts namely TasT Training Cycle, Neural Network Training Module, Operant Conditioning Theories working together to generate the desired output as trained individuals who are capable to train others in turn. Details of sub parts are explained in the paragraphs given below.

8.1 Proposed System Core Features

- Learning to recognize presented numbers and their meanings
- Interactively learn to sketch learned numbers
- Encourage improvement on writing pace and clarity of sketched numbers
- Learning age appropriate math for carrying out the daily activities

8.2 Proposed Trainees as Trainers Model (TasT)

The working principle of TasT model is depicted in Figure 5Figure 5 below:
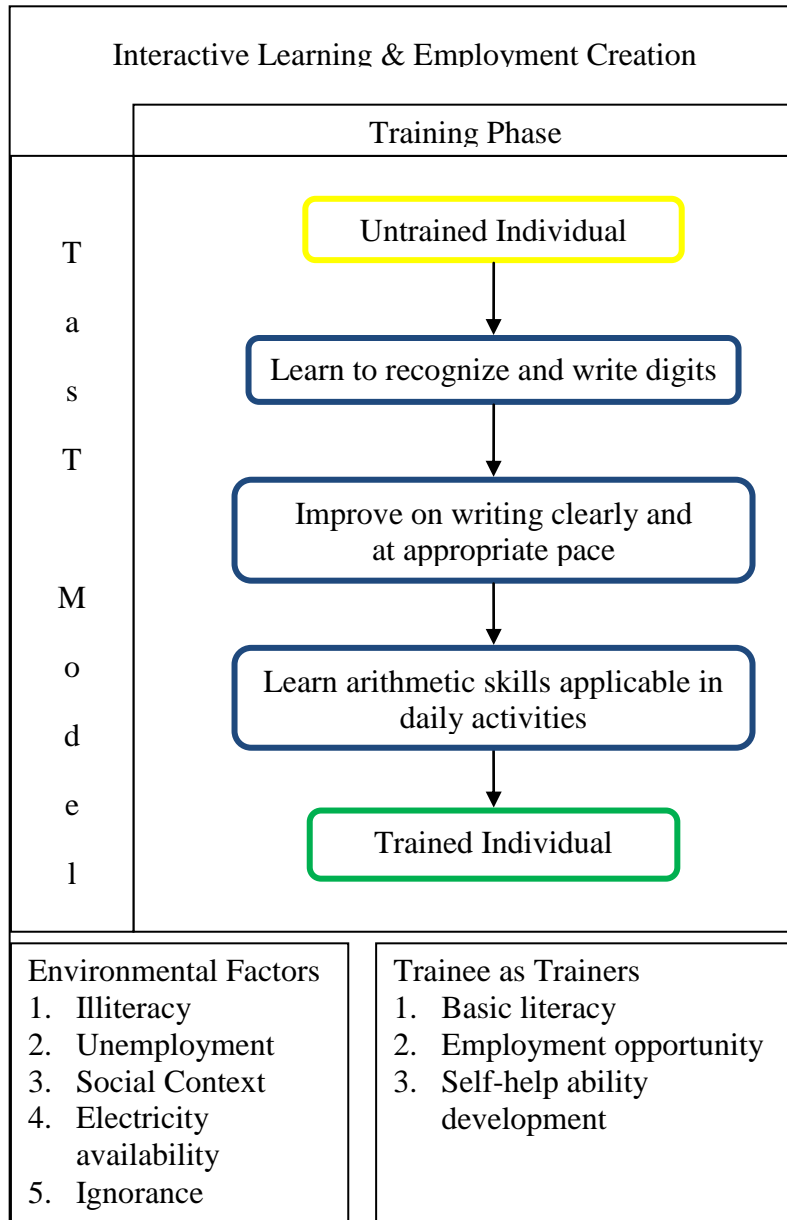

Figure 5 - Trainees as Trainers Model (TasT)

Sole motto of executing TasT model is learning digits by the trainees such that they can train others. The major role players or actors of the model are Trainees and Trainers. Trainers could be normal computer literate people for the first cycle. Trainees of the first batch could be

male/female of marginalized population of developing world who are not literate. To start off the project, the first batch of the trainees would be trained from normal computer literate people. The first batch of trainees is entering into the transformation phase. Later, those trained people would train local people so that there would be the real participation and visible outputs as well. Now, the trainees have entered into the productive phase.

Furthermore, selection of appropriate training methods is an important area of research in training and development. In this study, as discussed earlier in the literature review section, operant conditioning behaviorist theory fits in as a motivational package for speeding up the pace of learning for the targeted group of people. Markings were done for successful learning and negative markings for unsuccessful learning and after completely learning all digits, the learners get promoted to trainers. Details are described in the following section 8.2.1.

8.2.1   B.F Skinner Box

Positive Reinforcement	Negative Reinforcement
Score of participant is added up after each correct digit learning with "*Congratulations*" message. The score with congratulations message is a positive condition for the participant. The participant submits a correct digit, and again receives score. The participant's behavior of learning digits is strengthened by the consequence of getting higher scores.	A participant is learning digits and immediately receives a *Try Again* Option with a *buzzer* noise. The buzzer noise is a negative condition for the participant. The participant presses Try Again Option and retries wit digit learning and the buzzer stops. The participant receives another Buzzer, presses the Try Again Option again, and again the Buzzer stops. The participant's behavior of pressing the Try Again Button is strengthened by the consequence of stopping the buzzer.
Positive Punishment	Negative Punishment
A participant learns digit and receives a *negative score* with each two consecutive wrong attempts. The negative score is a negative condition for the participant. The participant commits the mistake again	A participant presses *Quit Button* on the UI in the application and nothing happens. Neither a positive nor a negative condition exists for the participant. The participant presses the Quit Button again and again

and again receives a negative score. The participant's behavior of committing mistakes while learning digits is weakened by the consequence of receiving a negative score.	nothing happens. The participant's behavior of pressing the button Quit is weakened by the consequence of not experiencing anything positive or stopping anything negative.

Figure 6 – B.F Skinner box

In Figure 6 above, four categories of operant conditioning are illustrated according to the experiment being carried out while testing the effectiveness of the SILECT tool used for the teaching digits to different age group individuals with minimum or no familiarity with digits.

8.3 Proposed System

8.3.1 Software

A software application, named "Nepali Handwriting Recognition for SILECT (2012)", has been developed implementing concepts as discussed in section 6.5.1. User interface of the software consists of basic elements for writing digit using touch/pen input, a predict button for assigning a digit label for the image, and a save button for collecting handwriting samples for the neural network training. During digit-learning phase, the user would write or draw the digit in the drawing area. The software would predict what digit the user has written. During handwriting samples collection phase, the same application would be used to save the images of digits drawn on the application. Application has been developed using Netbeans IDE and written in Java language making it independent of operating system installed on a pc. Screenshots of the application running in MS Windows environment is presented as Figure 7.
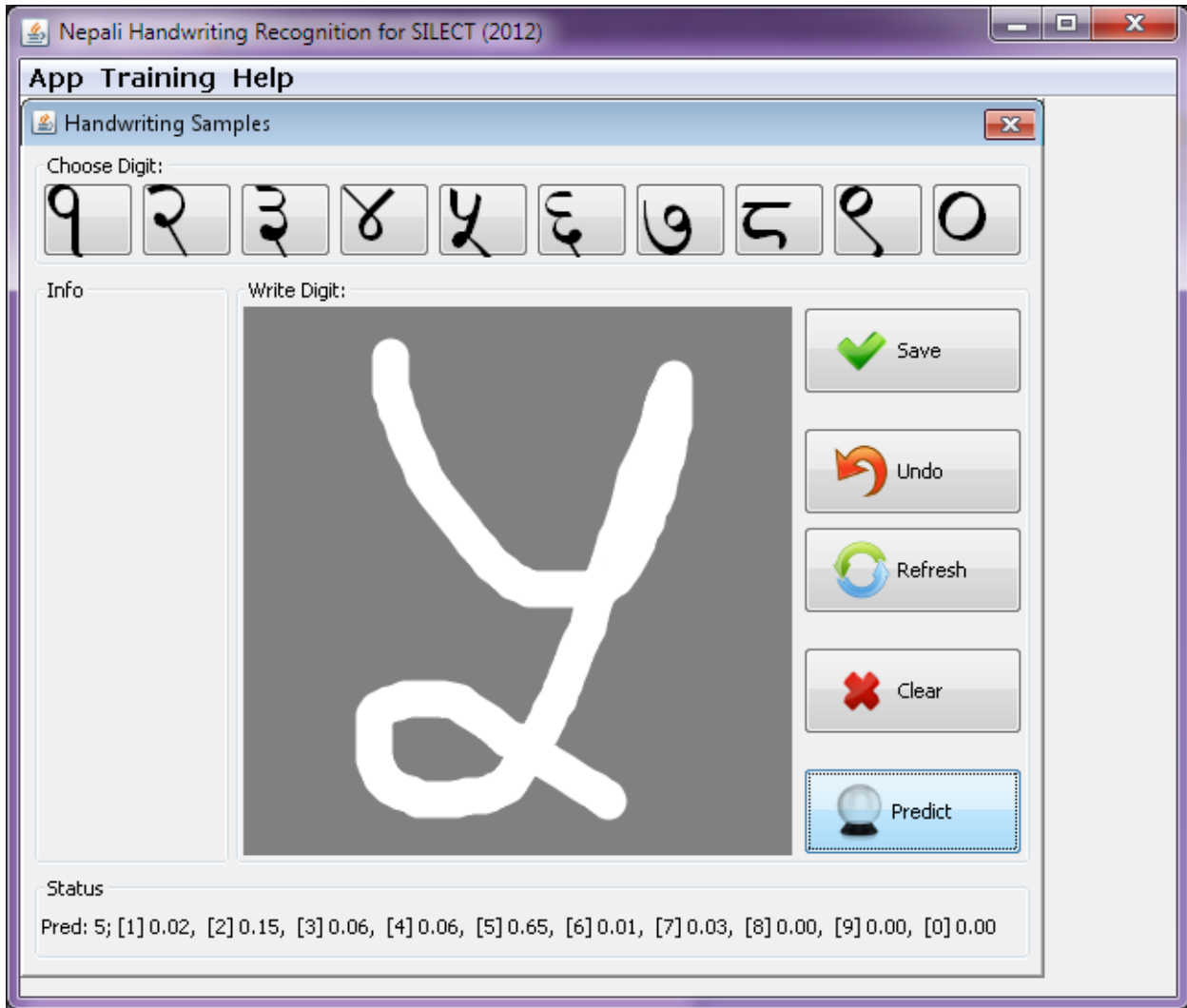
Figure 7 - Screenshot of Application for Nepali Handwriting Recognition

Obtaining neural network parameters/weights consists of retrieving samples of digits collected during data collection phase. The sample data is fed into neural network training procedure written for execution on Octave software. The parameters are saved into a file for use with "Nepali Handwriting Recognition" application. This process of calculating parameters happens before the software is presented to the end user.

8.3.2 Hardware

A basic computer set with capabilities described in following section is required to run the software application mentioned in section 8.3.1. The applications are selected from a pool of

open source alternatives running on minimum cost hardware, thus lowering overall cost of the system.

8.3.3 Hardware/Software Requirements

- Hardware:
  - PC capable of audio playback
  - Touch Screen Input Device or Pen Input Device
- Software:
  - Operating system: Linux with GUI desktop (preferred)
  - Supporting applications: Octave 3.4.3, Java Runtime Environment 1.7

8.3.4 Block Diagram

1. User draws/writes digit on the drawing area
2. Saving samples during data collection
3. Training Neural Network with collected data
4. Storing the best set of weights for 5
5. Application receiving digit's image from a learner (end user) and predicting the digit drawn as classification
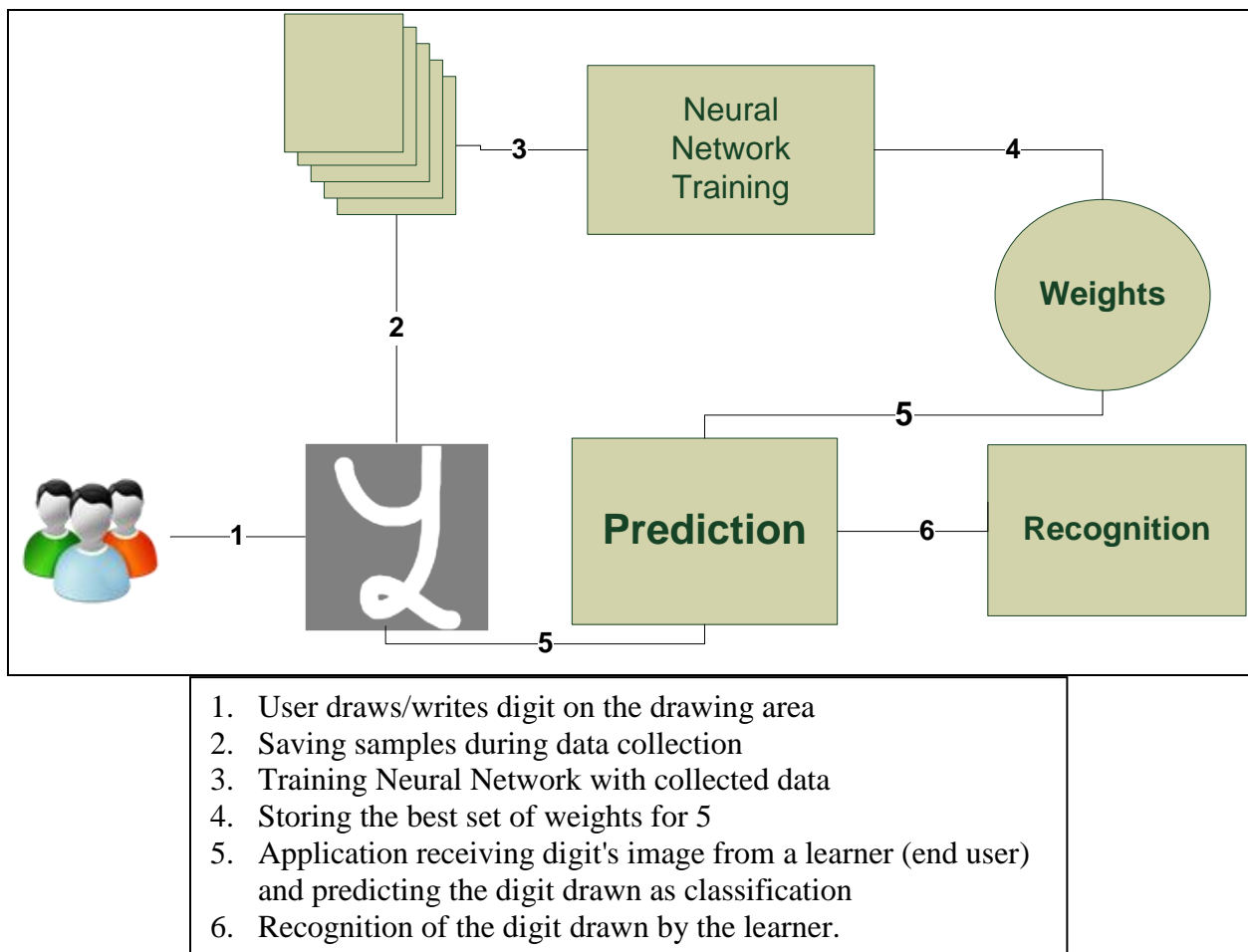6. Recognition of the digit drawn by the learner.

Figure 8 - Proposed System - Basic Block Diagram

9 Data Collection and Analysis

The sample data for training neural network were obtained by writing of sequence of digits ۱-۲-۳-۴-۵-۶-۷-۸-۹-۰ ten times and repeated after an hour. Individuals were also instructed to choose random digits to draw random number of times. To ensure variation of handwritten digits, different individuals of different age groups (6 - 10: 8 people), (25 - 30: 5 people), (50-70 : 5 people) were included. Group of individuals in similar age-group were instructed to write samples in a batch so as to ensure partial similarity among writings. The similarity and differences in writing styles makes rich set covering diverge writing patterns which allows neural network parameters to generalize well over new test cases. A total of 1,402 samples were collected of which 842 were used as training set, 280 were used as validation set, and 280 were used as test set.

Training of neural network was performed over training set with and validated over validation set. The learned parameters were used to test the performance of the neural network.

10 Results and Conclusion

Result of testing neural network over test set produced accuracy of 81%. The lower accuracy can be attributed to smaller number of hidden units, empirically chosen to reduce overall computation on the targeted low cost hardware.

During the data collecting phase among age group of 6-10, a number of individuals who have already submitted samples were keen on teaching remaining individuals write properly on the drawing area. This behavior further emphasize the idea of TasT model, discussed in section 8.2, that once an individual is trained, he/she can train new individuals eager to learn and the process can repeat itself number of times enhancing learning and teaching experience. A group of individuals who were intervened by the SILECT system were more enthusiastic in learning numerals and had gained a capability to teach numerals to others using ICT tool.

From the above discussions, it can be inferred that SILECT System that is proposed is quite successful in providing an interactive learning by teaching methodology in developing countries context based upon various multidisciplinary concepts from operant conditioning theories to neural network theories, and from education to people and participation.

11   Further Discussions

Mentioning some areas of further works comprises of improvising accuracy of digit recognition by: experimenting with size and structure of neural network (activation function, hidden units, etc); increasing training sample size etc. Furthermore, education and economic independence being interrelated and are both long term investments which require their own sweet period of time to realize the desired outcomes. Can we deploy ICT tool like SILECT elaborated in this paper in developing regions to fill in the gap so that problems of learning and earning could be minimized at least in smaller scale or to a specific micro target group? The authors leave this question to floor for further discussions.

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