DEVELOPMENT OF AN ANDROID BASED REAL-TIME IMAGE RECOGNITION APPLICATION USING CONVOLUTIONAL NEURAL NETWORK ALGORITHM: ADDRESSING CHALLENGES IN MOTHER TONGUE-BASED OF MULTILINGUAL EDUCATION

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Abstract - MTB-MLE teachers encountered several challenges and used similar strategies in teaching. Some of the challenges encountered by the teachers in MTB-MLE are lack of materials written in Mother Tongue and lack of vocabulary. Teachers use strategies such as translating instructional materials to mother tongue. Therefore, the researchers conducted a research on the aforementioned problem to develop a Convolutional Neural Network algorithm classification model and applied its concept on the development of an android-based application that will classify and recognize local vegetables that will help as additional instructional material for MTB-MLE Teachers. Multimethod research approach was utilized in the study. The researchers also employed phenomenological inquiry and data saturation criterions. Thematic Analysis was used to analyze qualitative data. The method of analysis were used to help the researchers move from a broad reading of the data toward discovering patterns and framing global themes. The experimentations are performed by using 449 vegetable images. The data sets were divided into 3 classes, potato (Solanum tuberosum) with 125 images, tomato (Lycopersicum esculentum) with 163 images and bitter gourd (Momordica charantia L. Amargoso) with 161 images, respectively. Each image is 300 by 300 pixels in dimensions and in JPG format. Based on the experiment conducted the model gained an average of 92.8 % accuracy. Furthermore, the application would be helpful to the teachers as an additional learning material and can be used for formative tasks.

Keywords: MTB-MLE, Convolutional Neural Network Algorithm, Mother Tongue-Based Of Multilingual Education,Image Recognition

I. INTRODUCTION

Studies show that MTB-MLE teachers used similar strategies such as translation of target language to mother tongue, and it appears as a challenge to teachers since they lack of vocabulary and limited materials are written in mother tongue. A recent World Bank Education Note (Bender et al., 2005) labels the use of colonial languages as media of instruction as one of the “non-productive practices that lead to low levels of learning and high levels of dropout and repetition” and deems this “the biggest challenge to Education For All” (Bender et al., 2005, p. 1). According to the same Note, mother tongue instruction results in (i) increased access and equity, (ii) improved learning outcomes, (iii) reduced repetition and dropout rates, (iv) sociocultural benefits, and (v) lower overall costs (Bender et al, 2005).

There are records and reports about the impact of technology in education. There are several research that has been conducted on the advantages of using technology in education and to formulate ideas that will enhance learning environment that technology provides in the classroom especially in Mother Tongue-Based of Multilingual Education (Jhurree, 2005). According to Dubria, Manarang and Martinez (2017), there are problems encountered by the teachers in MTB-MLE which are lack of materials written in Mother Tongue, lack of vocabulary, and the influence of social media to Pupils. It is also a challenge to teachers since they have to translate stories, songs, poems, workbooks, worksheets and other instructional material to mother tongue. Similar study has been conducted that the teachers used strategies such as translation of target language to mother tongue, utilization of multilingual teaching, utilization of lingua-franca, improvisation of instructional materials written in mother tongue, remediation of instruction, and utilization of literary piece written in mother tongue as motivation. Some problems encountered by the teachers in implementing mother tongue – based instruction include absence of books written in mother tongue, lack of vocabulary, and lack of teacher-training (Lartec, Belisario, Bendanillo, et.al., 2014). Nevertheless, the studies indicated that an image recognition application that will automatically classify and recognize things and displays the name to mother-tongue will be of great help to teachers as additional learning materials.

Image recognition is attained with the combined elements of machine vision, hardware and software to identify objects, places, people, writing and actions in images. (Rouse, Definition: Image Recognition, 2017) The software is a form of artificial intelligence that requires deep learning, commonly known as neural networks, concerned with emulating the human being's method to gain different types of knowledge to automate predictive analytics. (Rouse, Definition: Deep Learning, 2018) There are different kinds of neural networks however the Convolutional Neural Network was selected for this study wherein the scanned images were analyzed to enable recognition and classification of local vegetables. Convolutional Neural Networks are very similar to ordinary Neural Networks; they are made up of neurons that are learnable weights and biases (cs231n.github.io, ND).

The application was developed using Tensor Flow, an open source software library for high performance numerical computation. Its flexible architecture allows easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices. Originally developed by researchers and engineers from the Google Brain team within Google's AI organization, it comes with strong support for machine learning and deep learning and the flexible numerical computation core is used across many other scientific domains (tensorflow.org, ND).

The present study focused on local vegetables and proposed a scheme for automated recognition by analyzing features from digital images of the vegetables that will be used as additional learning material for MTB-MLE teachers.

II. STATEMENT OF THE PROBLEM

Previous studies focused on the use of classification and recognition to present a model for image recognition on different platforms and on different specific areas of the world were the researchers are based. Based on the literature review, limited studies have been conducted in the Philippines on classification and recognition of local vegetables that will help as additional instructional material for MTB-MLE teachers. Therefore, the researchers conducted a research on the aforementioned problem to develop a Convolutional Neural Network algorithm classification model using Tensor flow and applied its concept on the development of an application that will classify and recognize local vegetables that will help as additional instructional material for MTB-MLE Teachers. More specifically the researchers sought to answer the following questions,

1) What are the challenges of MTB-MLE teachers of using mother tongue as mode of instruction in teaching?
2) What are the strategies used by the teachers in implementing mother tongue – based instruction in a classroom?
3) What is the accuracy rate of the developed model for image classification and recognition of local vegetables?
4) What is are the possible impact of the Android Based Image Recognition using Convolutional Neural Network Algorithm application to MTB-MLE teachers?

III. REVIEW OF LITERATURES

In the past years we have seen an impressive arise in the use of machine learning techniques to build predictive models. According to Behera (2016) on his article about the Rapid Development and Deployment of Machine Learned Models, in the vastly evolving Predictive analytics tools, more and more applications are using machine - learned models to cater real world problems. This trend will continue to grow.

Because of new computing technologies, machine learning today is not just like machine learningof the past. It started from pattern recognition and the theory that machines can learn without being programmed to perform specific tasks; researchers interested in artificial intelligence wanted to see if computers could learn from data. According to sas.com (N.D.), the iterative aspect of machine learning is important because as models are exposed to new data, they are able to independently adapt. They learn from previous computations to produce reliable, repeatable decisions and results. Machine learning is considered a science that is not new but one that gained fresh momentum.

There are many recent announcements of deep learning technology used by Google, IBM, Microsoft and Facebook and private companies such as H2O among others and now some of those technologies are being open-sourced by enterprises. Recently, Google Brain Team has released Tensor Flow, an open-source library written in python, C++ and CUDA. At a high level, TensorFlow is a Python library that allows users to express arbitrary computation as a graph of data flows. Nodes in this graph represent mathematical operations, whereas edges represent data that is communicated from one node to another. Data in TensorFlow are represented as tensors, which are multidimensional arrays. Although this framework for thinking about computation is valuable in many different fields (Buduma, 2018). TensorFlow is primarily used for deep learning in practice and research from financial services, health care, oil and gas, government, marketing sales, transportation and even in education.

For many years, technology plays significant role in improving education specially in the Philippines. According to Reodique (2017) on an article titled "How DepEd is digitalizing Philippines' Education sector", Department of Education, as one of the largest agencies in the country is facing a challenge on how to be flexible enough to keep pace and innovate the delivery of education in the vast changing world. Consequently, there are number of programs and projects fell short of objectives. From the huge backlogs of the construction of classrooms, shortage of teachers and to shortage of learning materials. On the other note, implementation of the Mother-Tongue Based of Multilingual Education became an additional problem especially to teachers.

According to Metila, Predilla and Williams (2017), Mother-Tongue Based of Multilingual Education (MTB-MLE) policy in the Philippines involves implementation of local mother tongue as the language of instruction from the first three years in school (K - 3) and official language (English and Filipino) as the language of instruction after grade 3. Previously, the early education used English and Filipino as the mode of instruction in the classroom and mother tongue is being used to assist the learners and teachers. On the same note, there are problems that were encountered pn the implementation of the policy.

A study by Dubria, Manarang and Martinez (2017) on the strategies and problems of teachers in using MTB-MLE. Based on the teachers viewpoints, it affects the Pupil's academic progress and classroom participation. The result show that teachers have to translate stories, songs, workbooks, worksheets and other instructional materials to mother tongue, which then also a problem since teachers lack materials written in mother tongue and specially some teachers have limited vocabulary on mother tongue.

From the above literatures, the researchers hypothesized that developing an image recognition model and implementing in an android – based application is feasible and would be useful for as an additional instructional material for MTB-MLE teachers. Following are the related studies conducted by different researchers on the development of schemes or models using neural network algorithms.

IV. METHODS AND PROCEDURES

A. *Research Design*

The researchers employed phenomenological inquiry and data saturation criterions and arrived having five (5) interview subjects. The researchers utilized the design to know the challenges and strategies experienced by the MTB-MLE teachers in teaching mother tongue. The result gave insights to the researchers on the need of developing an application for image recognition. Moreover, an experimental design has been used to determine the accuracy of the model and to test the reliability of the application.

B. *Participants of the Study*

Since the classification model developed in the study was implemented for the development of the application that will be used as an additional learning material for Mother Tongue-Based education. The researchers chose MTB-MLE teachers as the participants of the study considering that the researchers wanted to identify the challenges and strategies used by the teachers in the classroom on account of identifying the importance of developing the application. Having 5 interview subjects for the study was arrived at based on phenomenological inquiry and data saturation criterions. According to Creswell (1998), phenomenology requires in-depth interviews from 3 to 13 subjects. Below is the list of the participants of the study.

TABLE I. PARTICIPANTS OF THE STUDY

Participants Code	**Participants Profile**			
	Position	***Age***	***Gender***	***Name of School***
P1	Teacher 1	38	Female	San Jose Central School
P2	Teacher 1	41	Female	San Jose Central School
P3	Teacher 1	39	Female	San Jose Central School
P4	Teacher 1	39	Female	Pawing Elementary School
P5	Instructor 1	24	Male	Integrated Laboratory School - LNU

C. Data Collection Methods

A semi-structured in-depth interview (Patton, 1990) was used as data gathering tool. Their sharing revolved around the questions, "Based on your experiences, what are the challenges in teaching using MTB-MLE?", "What are the strategies that you used in using MTB-MLE to address the challenges?" The interview was considered suitable in this study in order to determine participants' challenges and strategies based on there experiences (Sharma, 1994 as cited by Ndamba, 2008). Mobile phone recordings were used during the interview.

In addition, the researchers demonstrated the application to the teachers to gather some insights from the participants on the impact or possible benefits of the application to MTB-MLE teachers as an additional learning material in the classroom.

For the development of the model, the researchers trained the data sets in Tensor Flow and analyzed the behavior of the data using Tensor Board. An experiment was conducted to determine the accuracy of the model using the application.

D. Data Analysis

The recorded interviews were transcribed into field texts. Thematic Analysis was used to analyze qualitative data. The method of analysis was used to help the researchers move from a broad reading of the data toward discovering patterns and framing global themes (Howitt & Cramer, 2007). The method enabled researchers to develop a deeper appreciation for the participants' experiences on the challenges and strategies used in teaching MTB-MLE. Data sets were trained in Tensor Flow and applied the Convolutional Neural Network Algorithm and wrapped to run on android devices. Then analyzed the trained model in Tensor Board to much understand the behavior of the trained model. To determine the accuracy of the application an experiment has been conducted. Different images and actual vegetables have been used to scan and recognize. Below are the images used in the experiment.

Figure 1 Images from the Internet

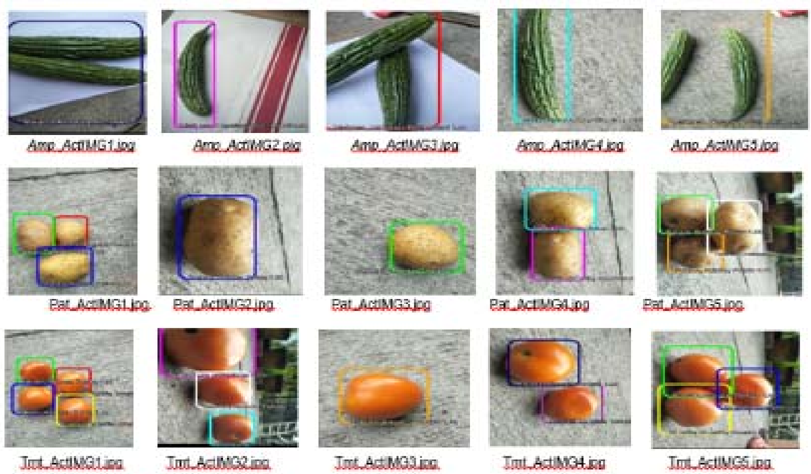

Figure 2 Actual Images used In the Experiment

E. Research Procedure

1) Image samples

Colored images of the vegetable samples were acquired and saved digitally using an OPPO A57 mobile phone and the images were uploaded to a laptop computer.

The experimentations are performed by using 449 vegetable images. The data sets were divided into 3 classes, potato (Solanum tuberosum) with 125 images, tomato (Lycopersicum esculentum) with 163 images and bitter gourd (Momordica charantia L. Amargoso) with 161 images, respectively. Each image is 300 by 300 pixels in dimensions and in JPG format. Sample images of each class are shown below.

Figure 3. Sample of vegetable images belonging to 3 classes

2) Convolutional Neural Network

Convolutional Neural Networks are very similar to ordinary Neural Networks, they are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity. The whole network still expresses a single differentiable score function: from the raw image pixels on one end to class scores at the other. And they still have a loss function (e.g. SVM/Softmax) on the last (fully-connected) layer and all the tips/tricks we developed for learning regular Neural Networks still apply (cs231n.github.io, ND).

ConvNet architecture creates an assumption that the input layer are images. A CNN transforms its neuron into three dimension (height, width, depth) form. It has such an architecture that each volume of transform to another volume (Batvia, Patel, & Vasant, 2017).

The study applied the CNN algorithm for individual image classification. Then image classification results are combined to produce observation classifications. Below is the sample of a CNN architecture.

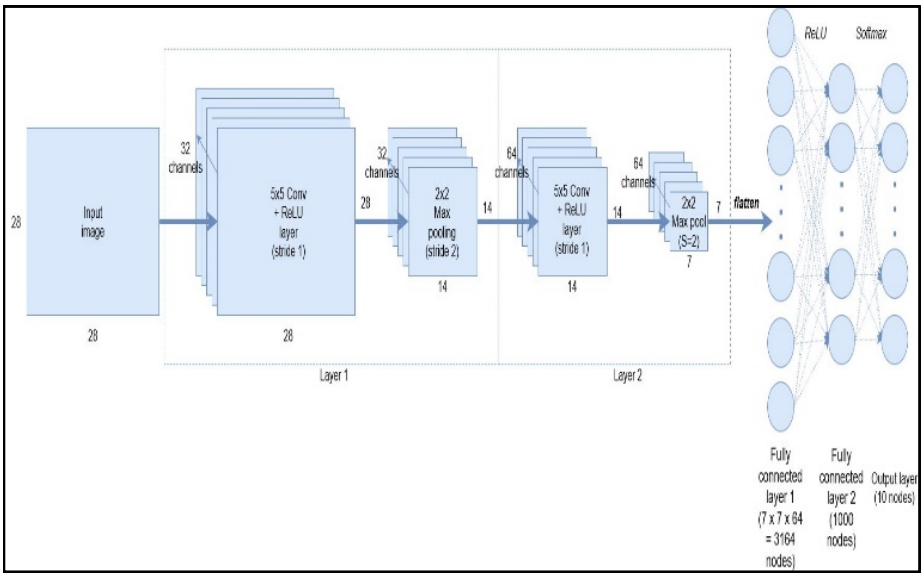

Figure 4. Convolutional Neural Network Architecture

There are mainly three types of layers which are used to build a CNN; (a) Convolutional layer (b) Pooling layer (c) Fully connected layer and one more layer is used called Normalization layer (Karpathy, ND as cited by Batvia, Patel, & Vasant, 2017). The convolutional layer does the most part of the computation and considered as the core part of the algorithm. The layer does the heavy work on the inputs which includes taking a volume of input combining them by performing dot products (filters) on them and giving output volume block of image. Pooling layer is commonly inserted after a period regularly. Its task is to gradually reduce the spatial size of the representation which in turn reduces the number of parameters in computation in the network. The Fully Connected layer is the last layer and it has full connections to all the activations from the previous layers (Karpathy, ND as cited by Batvia, Patel, & Vasant, 2017).

3) Tensor Flow

The researchers utilized Tensor Flow for image classification. The tensor Flow run-time is a cross – platform library. Figure 4.0 illustrates the general architecture.

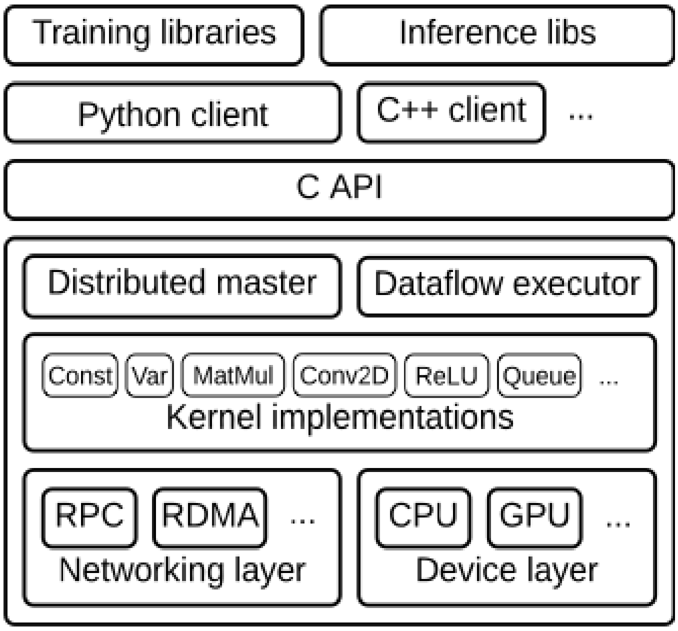

Figure 5. General architecture of Tensor Flow

The client defines the computation as a data flow graph. It also initiates graph execution using a session. Distributed master prunes the subgraph from the graph, as defined by the arguments to Session.run(). Then partition the sub graph into multiple pieces that run in different processes and devices. Moreover, the worker services schedule the execution of graph operations using kernel implementations appropriate to the available hardware such as CPUs, GPUs, etc. It is also responsible for sending and receiving operation results to and from the worker services. Lastly, kernel implantations perform the computation for individual graph operations.

V. RESULTS AND DISCUSSIONS

To validate the model for the development of the android based image recognition using convolutional neural network algorithm, a set of 449 images were used. The images were divided into 3 classes, potato (Solanum tuberosum) with 125 images, tomato (Lycopersicum esculentum) with 163 images and bitter gourd (Momordica charantia L. Amargoso) with 161 images, respectively. The data sets were divided into training data and test data, 90.0 % for the training data and 10.0 % of the images for test sets.

The overall accuracy from the result of the experiment can be seen in Table 2.0 and the behavior of the model is also presented. Moreover, the result from the interviews conducted are also presented and were analyzed using thematic analysis.

TABLE 2. OVERALL ACCURACY RATE OF THE ANDROID BASED IMAGE RECOGNITION APP FOR THE THREE (3) VEGETABLES

Overall Accuracy Rate	
Vegetables	***Accuracy rate***
Bitter Gourd, *Ampalaya, Mariguso*	99.6%
Kamatis, Kamatis, Tomato	92.2%
Patatas, Patatas, Potato	86.6%
Total (mean percentage)	92.8%

The above table shows the overall accuracy rate of the android based image recognition application using convolutional neural network. Since there are only 404 images out of 449 were used in training and the researchers set the steps to 400 thousands, the application gained the 92.8 mean percentage of the total accuracy rate of each images. This mainly due to unbalanced patterns, labeling the images and attributes that will uniquely identify each vegetable.

Based on the study of Wijesingha and Marikar (2011) on the Automatic Detection System for the Identification of Plants Using Herbarium Specimen Images, providing balanced dataset is a major issue. This is related to the number of input samples, since the study of Wijesingha and Marikar (2011) used 79 samples only and gained the classifier of 85.0 % accuracy. Furthermore, the number of classes, the statistics behind those sample sets, or not following the true prior probability distribution of input data samples are also factors on gaining low accuracy of a model. Compared to the previous studies, the accuracy of 92.8 % gained is promisingly high.

However, further development and more samples are required to gain a more accurate model. Nevertheless, the android based image recognition using CNN algorithm has a great potential for real - time image recognition and will greatly help the MTB-MLE teachers in the classroom.

Below are the tables to give the details of the result of the experiment.

TABLE 3 TEST SCENARIOS FOR APPLICATION TESTING USING DIFFERENT IMAGES OF BITTER GOURD (AMPALAYA)

Images	**Test scenarios for application testing**		
	Expected Result	***Actual Result***	***Success Rate (%)***
Amp_EXPImage1.JPG	Bitter Gourd, Ampalaya, Mariguso	Bitter Gourd, Ampalaya, Mariguso	100.0 %
Amp_EXPImage2.JPG	Bitter Gourd, Ampalaya, Mariguso	Bitter Gourd, Ampalaya, Mariguso	98.0 %
Amp_EXPImage3.JPG	Bitter Gourd, Ampalaya, Mariguso	Bitter Gourd, Ampalaya, Mariguso	100.0 %
Amp_EXPImage4.JPG	Bitter Gourd, Ampalaya, Mariguso	Bitter Gourd, Ampalaya, Mariguso	100.0 %
Amp_EXPImage5.JPG	Bitter Gourd, Ampalaya, Mariguso	Bitter Gourd, Ampalaya, Mariguso	100.0 %
Total(mean percentage)			**99.6 %**

Table 3 shows the test scenarios of the application for image recognition of Bitter Gourd. Five experiments have been executed. The model was able to recognize the first, third, fourth and fifth images with the probability of 100.0 %. However, the second image got 98.0 % accuracy only, this is due to the green environment of the whole image. Nevertheless, the mean accuracy of the bitter gourd (ampalaya) is 99.6 %, this is a good indicator that the model can recognize the image with a promising accuracy.

TABLE 4 TEST SCENARIOS FOR APPLICATION TESTING USING DIFFERENT IMAGES OF TOMATO (KAMATIS)

Images	**Test scenarios for application testing**		
	Expected Result	***Actual Result***	***Success Rate (%)***
TMT_EXPImage1.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	100.0%
TMT_EXPImage2.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	100.0%
TMT_EXPImage3.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	72.0%
TMT_EXPImage4.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	91.0%
TMT_EXPImage5.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	98.0%
Total(mean percentage)			**92.2%**

Based on the results from table 4.0, TMT_EXPImage1.JPG and TMT_EXPImage2.JPG got an accuracy rate of 100.0 %. TMT_EXPImage4.JPG gained a 91.0 % accuracy and 98.0 % accuracy for TMT_EXPImage5.JPG. While TMT_EXPImage3.JPG got the lowest accuracy of 72.0 %. Classifiers such as the color and shape of the tomato are factors which influenced the accuracy of the model.

TABLE 5 TEST SCENARIOS FOR APPLICATION TESTING USING DIFFERENT IMAGES OF POTATO (PATATAS)

Images	**Test scenarios for application testing**		
	Expected Result	***Actual Result***	***Success Rate (%)***
PAT_EXPImage1.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	99.0%
PAT_EXPImage2.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	81.0%
PAT_EXPImage3.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	61.0%
PAT_EXPImage4.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	96.0%
PAT_EXPImage5.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	96.0%
Total(mean percentage)			**86.6%**

Table 5 presents the result form the experiment conducted on the different images of potato. None of the images got a 100.0 % accuracy, PAT_EXPImage1.JPG gained 99.0 %, PAT_EXPImage2.JPG got 81.0 %, 61.0 % for PAT_EXPImage3.JPG, PAT_EXPImage4.JPG gained an accuracy of 96.0 % as well as PAT_EXPImage5.JPG. Since shape and color are some of the classifiers to recognize the vegetables, this implies that the model is slightly confused of the images, either tomato or potato.

TABLE 6 TEST SCENARIOS FOR APPLICATION TESTING USING AN ACTUAL BITTER GOURD (AMPALAYA)

Images	**Test scenarios for application testing using the actual vegetable**		
	Expected Result	***Actual Result***	***Success Rate (%)***
Amp_ActIMG1.JPG	*Marigoso, Ampalaya, Bitter Gourd*	*Marigoso, Ampalaya, Bitter Gourd*	99.0%
Amp_ActIMG1.JPG	*Marigoso, Ampalaya, Bitter Gourd*	*Marigoso, Ampalaya, Bitter Gourd*	82.0%
Amp_ActIMG1.JPG	*Marigoso, Ampalaya, Bitter Gourd*	*Marigoso, Ampalaya, Bitter Gourd*	89.0%
Amp_ActIMG1.JPG	*Marigoso, Ampalaya, Bitter Gourd*	*Marigoso, Ampalaya, Bitter Gourd*	98.0%
Amp_ActIMG1.JPG	*Marigoso, Ampalaya, Bitter Gourd*	*Marigoso, Ampalaya, Bitter Gourd*	100.0%
Total(mean percentage)			**93.6%**

Table 9.0 indicates that only Amp _ActIMG5.JPG got a 100.0 accuracy. 99.0 % for Amp_ActIMG1.JPG, 98.0 % for Amp_ActIMG5.JPG, 98.0 % for Amp_ActIMG4.JPG and Amp_ActIMG2.JPG got the lowest accuracy of 82.0 %.

TABLE 7 TEST SCENARIOS FOR APPLICATION TESTING USING AN ACTUAL TOMATO (KAMATIS)

Images	**Test scenarios for application testing using the actual vegetable**		
	Expected Result	***Actual Result***	***Success Rate (%)***
Tmt_ActIMG1.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	100.0%
Tmt_ActIMG2.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	90.5%
Tmt_ActIMG3.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	100.0%
Tmt_ActIMG4.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	100.0%
Tmt_ActIMG5.JPG	*Kamatis, Kamatis, Tomato*	*Kamatis, Kamatis, Tomato*	94.5%
Total(mean percentage)			**97.0%**

Table 7 indicates that recognizing tomato has higher accuracy of 97.0 % than of bitter gourd. Tmt_ActIMG1.JPG, Tmt_ActIMG2.JPG and Tmt_ActIMG4.JPG gained a 100.0 % accuracy. However, Tmt_ActIMG2.JPG and Tmt_ActIMG5.JPG gained 90.5 % and 94.5 % accuracy.

TABLE 8 TEST SCENARIOS FOR APPLICATION TESTING USING AN ACTUAL POTATO (PATATAS)

Images	**Test scenarios for application testing using the actual vegetable**		
	Expected Result	***Actual Result***	***Success Rate (%)***
Pat_ActIMG1.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	100.0%
Pat_ActIMG2.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	100.0%
Pat_ActIMG3.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	100.0%
Pat_ActIMG4.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	99.0%
Pat_ActIMG5.JPG	*Patatas, Patatas, Potato*	*Patatas, Patatas, Potato*	99.3%
Total(mean percentage)			**99.66%**

As presented in table 8, Potato gained an overall mean percentage of 99.66 % accuracy. This greatly shows that the model was able to recognize potato more accurately than the other vegetables. Moreover, Pat_ActIMG1.JPG, Pat_ActIMG2.JPG and Pat_ActIMG3.JPG gained a 100.0 % accuracy rate. While Pat_ActIMG4.JPG got 99.0 % and a higher of .3 % for Pat_ActIMG5.JPG.

1) Challenges of Mother Tongue-Based of Multilingual Education teachers

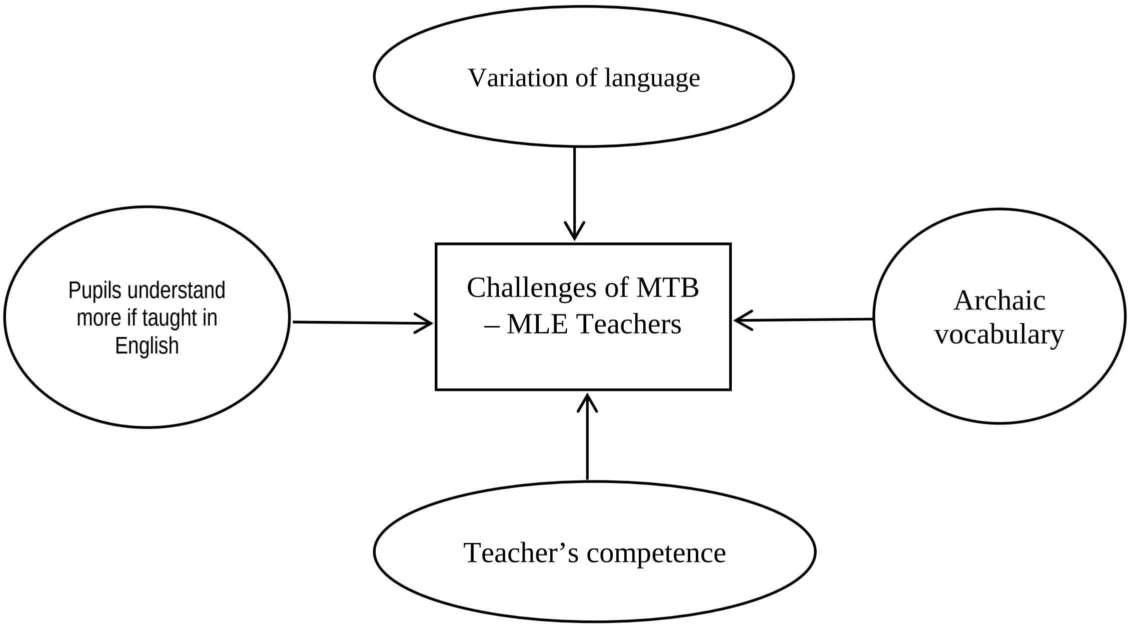

Figure 6 Thematic diagram of the challenges encountered by MTB – MLE teachers

There are four themes that were developed regarding the challenges encountered by the MTB – MLE teachers on the implementation of Mother Tongue – Based of Multilingual Education. These are (a) variation of language, (b) archaic vocabulary, (c) Teacher’s competence, and (d) Pupils understand more if taught in English.

Teacher’s competence includes lack of trainings, lack of vocabulary, and insufficient materials written in mother tongue. The participants felt that trainings and seminars for teachers should be provided regularly and academic support from the specialist on various issues in mother tongue teaching. According to Lartec, Belisoria and Bendanillo (2017), lack of vocabulary is considered to be the dearth of the words to use when delivering a message or information. There is no wide range of the words or phrases used in discussing the lesson using mother tongue; therefore, it is considered as one of the problems being encountered by the teachers. One of the participants stated *that “I am not fluent in Waray-waray, So there are uncommon terms in waray-waray which Pupils hardly understand ”*. Another participant said *“The vocabulary of the teacher in not enough because other teachers are not used in Winaray”*. A Master Teacher from Pawing Elementary School said that *“often teachers handling mother tongue based subjects don’t have the same type of waray-waray dialect and that is the major problem that occurs.”*. From the statement, their knowledge on different languages is not enough to deliver the lesson. In addition, the respondents are experiencing difficulties in teaching their pupils because they cannot think of the right word that is exactly the equivalent of the source language, putting them in a situation that will bring confusion to the pupils.

2) Strategies of Mother Tongue-Based of Multilingual Education teachers to address the challenges

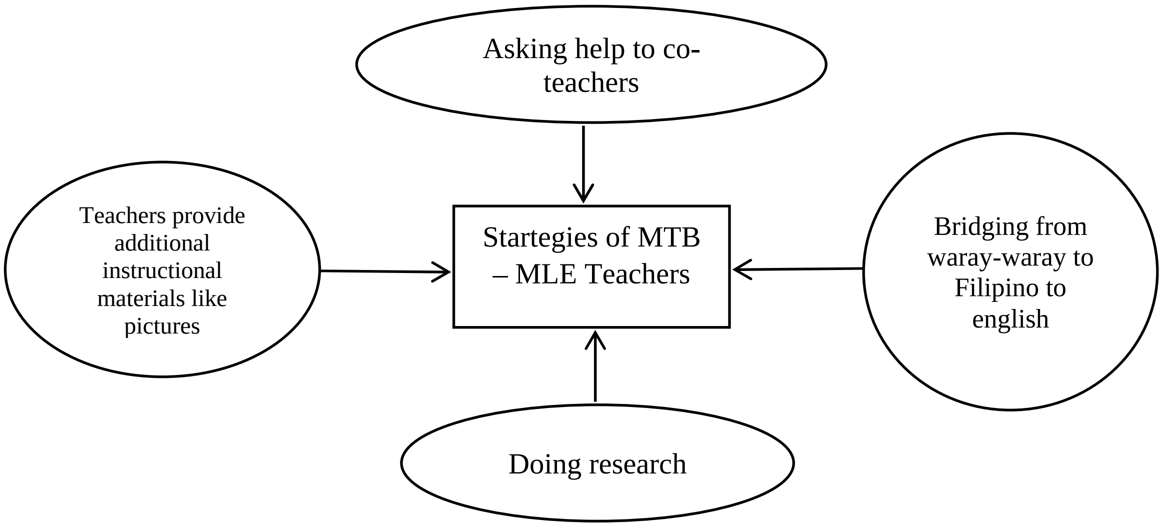

Figure 7 Thematic diagram of the strategies of MTB – MLE teachers

Based on the answers from the interview conducted on the strategies employed by teachers in the implementation of mother tongue – based for multilingual education, several themes emerged. These themes are (a) Asking help to teachers, (b) Doing research, (c) Bridging from waray-waray to filipino to English and (d) Teachers provide additional materials like pictures.

According to Burton (2013), translating words is beneficial to Pupils' learning through the use of Pupil's mother tongue since it bridges the Pupils to the lesson. It is also referred as the fifth language skill alongside with the four basic skills of learnings. From the participants view, translation is important because it will help the Pupils understand more if words are translated from mother tongue to different language where it meets the need of the Pupils. A participant from San Jose Central School called it as bridging, she stated *"What I am doing is that, bridging, Bridging from waray-waray to Filipino to English. Three (3), example, misay, pusa, cat. That is bridging."*. The statements indicate that are using translation to Pupils to fully understand the lesson. The statement shows that the teacher is using Waray-waray as a medium of instruction and if the Pupil doesn't fully understand the word, the teacher will translate the word into other language that the said pupil understands. A participant mentioned, *"We use instructional materials like pictures so that pupils will understand more."*.

As seen from the response above, translation can be applied in every aspect of learning. The researchers based their study on the seen abovementioned challenges and strategies – pupils understand more if translated to other language and teachers bridging the words from mother tongue to other dialects.

3) Impact of the Android – based Image Classifications Application using Convolutional Neural Network Algorithm

From the interview conducted, the participants said that the android based image recognition will be of great help to them as MTB-MLE teachers. It can be useful wherein it will serve as a drill activity to pupils, as formative task and it would be an advantage since the pupils can easily recognize the objects.

VI. CONCLUSION

The study confirms that an android based image recognition using CNN is relatively of great help to MTB-MLE teachers and will significantly address the challenges encountered and strategies employed in the classroom. Consequently, further development is required to increase the accuracy. Nevertheless, the findings indicate that the proposed feature extraction algorithm has a great potential for feature representation in this classification task.

VII.RECOMMENDATION

Based on the results, it is recommended to input more sample vegetables and steps in training the model to increase the accuracy of the application. Add more classes for the application and an additional feature such as voice recognition to address pupils who can't read yet and with colorful graphics of the application to attract pupils.

REFERENCES

[1] Andrej Karpathy. Convolutional Neural Networks for Visual Recognition. [Online]. Available http://cs231n.github.io/

[2] Behera, P. (2016). Rapid Development and Deployment of Machine Learned Models. Available from https://scoredata.com/rapid-development-and-deployment-of-machine-learned-models/

[3] Dubria, E. D., Manarang, C. N. T., Martinez, V.B., & Yambao, L.L. (2017)

[4] Howitt, D., & Cramer, D. (2007). Thematic Analysis. Research Methods in Psychology. Prentice Hall (2nd ed.). Retrieved from: http://wps.pearsoned.co.uk/ema_uk_he_howitt_resmethpsy_2/77/19811/5071812.cw/index.html

[5] Lartec, J. K. (2015). Strategies and problems encountered by teachers in implementing mother tongue-based instruction in a multilingual classroom. From https://s3.amazonaws.com/academia.edu.documents/44380307/4-Jane-K-Lartec-et-al.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53UL3A&Expires=1524637954&Signature=3M9%2Fwl9b5OmtEhOALLQXuYNfwck%3D&response-content-disposition=inline%3B%20filename%3DStrategies_and_Problems_Encountered_by_T.pdf

[6] Metila, R., Pradilla, L. A., & Williams, A. (2017). Investigating best practice in Mother Tongue-Based Multilingual Education (MTB-MLE) in the Philippines, Phase 3 progress report: Strategies of exemplar schools. Report prepared for Australian Department of Foreign Affairs and Trade and Philippine Department of Education. Melbourne and Manila: Assessment, Curriculum and Technology Research Centre (ACTRC).

[7] Reodique, A. (2017). How DepEd is digitalising Philippines' education sector. ComputerWorld.ph. Retrieved from https://www.computerworld.ph/tech/careers/how-deped-is-digitalising-philippines-education-sector/

[8] Dubria, E.D., Manarang, N.T., Martinez, V.B., Yambao, L.L., (2017). Strategies and Problems of Teachers in Using MTB-MLE. Retrieved from https://www.tesol.asia/15thconference/breakout-sessions-schedule/day-2-april-8-2017/strategies-and-problems-of-teachers-in-using-mtb-mle/

[9] Sahnnon, C. (2005). Technology in Education. International Education Journal, 2005, 6(4), 467-483. ISSN 1443-1475 © 2005 Shannon Research Press. From http://iej.cjb.net

[10] Tupas, R. (2015). Inequalities of multilingualism: Challenges to mother tongue-based multilingual education. Language and Education, 29(2), 112-124. From https://repository.nie.edu.sg/bitstream/10497/17671/1/LE-29-2-112.pdf