FISHNET: FISH IDENTIFICATION UNDER FISHERIES MANAGEMENT AREA 7 THROUGH IMAGE PROCESSING USING ALEXNET MODEL

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I INTRODUCTION

Background of the study

The Philippines is blessed with different natural resources. It has extensive coastlines, varied flora and fauna, fertile lands, and abundant mineral deposits. Furthermore, the Philippines is an archipelago made up of more than 7,000 islands with rich marine life. As a result, the nation's fishing industry is flourishing and supports the livelihood of many Filipinos. However, there are challenges in this industry as well. According to Philippine Statistics Authority (2016), the increase in the population coupled with the improved fishing technology brought stress to the country’s marine and coastal ecosystem, thereby affecting the fishery resource.

In response to this ongoing environmental concern, the government established Fisheries Management Areas (FMAs). It was created through the Fisheries Administrative Order No. 263 issued by the Department of Agriculture – Bureau of Fisheries and Aquatic Resources. It contains 12 Fisheries Management Areas (FMAs) covering all Philippine waters based on considerations of stocks boundary, range, administrative subdivisions, and distribution of fisheries. FMAs also provide for a science-based, participatory and transparent framework of governance. It is science- based as management decisions consider the status of fish stocks and other ecological considerations. (*Fisheries Management Areas*, n.d.)

The government, academe, and key stakeholders have shared responsibility in conservation and maintenance of the FMAs. Maintaining marine resources depends heavily on effective fishery management.

One role of FMA is monitoring the condition of fish species. Moreover, fish identification plays a vital role in the fish population protection and fish culture. According to Pudaruth et al. (2021), the accurate identification of the fish species is essential to every study. Accurate identification is necessary for evaluating fish stocks, capture, and seafood labeling. Ariganello et al. stated that the shape of fish's heads, the location of their mouths, the type and location of their fins, and their average adult size are some traits that distinguish them apart. When combined with other characteristics like geographic range, color patterns like vertical stripes or fin patches may also aid in differentiating fish.

Kirsch et al. (2018) affirmed that fish monitoring programs regularly collect, identify the species of the fish, and count the quantity of individual fish over time in order to make decisions regarding the management of natural resources. Therefore, species misidentification can have a negative impact on the usefulness of the information used to support these judgments.

Traditionally, observers or statistical researchers manually record the reported information. Here in the Philippines, the Philippine Statistics Authority conducts fisheries surveys by hiring researchers to visit sample fish landing centers for commercial and municipal fisheries. Additionally, statistical researchers interview aqua farm operators and fishermen. Tseng & Kuo (2020) claimed that human fatigue may contribute to inaccurate reporting. Furthermore, Ganaden et al. (2016) argued that the use of common names might be confusing because there are instances where various fish species are referred to by the same common name. This may result in misidentification, which could compromise accurate recording of particular fish catches and overall production.

Minimizing human mistakes during the process of fish observation and analysis is crucial in fishery education and calls for an automatic system detection. (Rum & Az, 2021)

Advancement in technology can be integrated in identifying fish species. With the aid of technology, monitoring will become accurate, automatic, and cost-effective. The study of Tseng et.al (2020) stated that some countries use electronic monitoring systems to track the fishing practices and identify the fish species harvested. However, this system still needs manual screening of videos. It is also costly and exclusive for large-scale fishing. A smartphone application can be utilized to identify fish species and know related information about them.

Smartphones have been widely used for different purposes. It is portable and users find it easy to navigate. As a result, mobile application development increased due to its use in various areas.

Mobile applications integrated various concepts of computer science, including image processing. Azadnia and Kheiralipour (2021) states that Image processing is a robust method in which a set of image procedures are used to reinforce the quality of the images. The image procedure utilizes to extract the image features. Furthermore, Image processing is a way to convert an image to a digital aspect and perform certain functions on it, in order to get an enhanced image or extract other useful information from it. (Team, 2021)

Recently, image processing has been applied to various fields. Padmappriya and Sumalatha (2018) states that some of the important applications of image processing in the field of science and technology include computer vision, remote sensing, feature extraction, face detection and optical character recognition. There is so much potential in utilizing image processing for solving problems.

In order to utilize image processing, certain features must be extracted and observed. To discover certain features, it might be more efficient to focus on small areas of the image than to scan the entire thing at once. This is the process in Convolutional neural networks. According to Thomas (2019), a Convolutional neural network (CNN) is a neural network that has one or more convolutional layers and are used mainly for image processing and classification.

Mishra (2020) stated that it also specializes in processing data that has a grid-like topology, such as an image. This type of deep learning model will be helpful in identifying fish species. One of the implementations of CNN is the AlexNet Architecture. According to Wei (2019), AlexNet is an incredibly powerful model capable of achieving high accuracies on very challenging datasets.

Based on the existing information and platforms, it will be possible to create a mobile application that will integrate image processing. This study will develop a mobile application that will automate the identification of fish species in Fisheries Management Area (FMA) 7. FMA 7 covers Quezon Province, Camarines Sur, Albay, Sorsogon, Masbate, Northern Samar, Biliran, Leyte, and Western Samar. The mobile application will not only help the researchers but also the consumers who need relevant information about the fish. Learners and experts who are interested to know more about the fish species found in FMA 7 will greatly benefit from this mobile application.

Objectives of the Study

The study primarily aims to develop a mobile application that identifies fish species belonging to Fisheries Management Area 7 through image processing using AlexNet Model.

Specifically, the study sought to answer the following:

1. Create a mobile application that enables to identify fish species under FMA 7 through phone camera, specifically: a) Kuwaw, b) Sapsap, c) Buraw, d) Turay and e)Turingan

2. Implement AlexNet Model for training and classification of gathered images through CNN Validation using the following evaluation metrics: a) Accuracy, b) Precision, c) Recall and d) Categorical Cross Entropy

3. Evaluation of developed system/application with compare to human

Scope and Limitations of the Study

The focus of this study is to create a fish species identification android app for Fisheries management area 7. The android app will be made since the researchers don’t have a paid apple developer account that will be used in distributing iOS apps on App Store. The researchers plan to develop an app that can determine a fish's species from an input image, specifically its local and scientific name. The app will also show related images after detection such as the same species or genus from the internet, and give relevant information about that species such as descriptions, genus, color, common places where it would probably be found, and seasonal or not. The input will be a real-time frame or a taken picture using a phone camera within the app then the captured frame will be analyzed using the AlexNet CNN model utilizing the soft attention-based algorithm for detection accuracy because according to Ju & Xue (2020), this operation chooses the features that are most crucial for classification and evaluates the significance of each feature thus helps facilitate the accuracy. As for the app to successfully identify the specific fish and its species, the input image must be stable (not blurred or moving), suitably illuminated, sufficiently close, and also to the greatest extent possible, have a clean background or clear aquatic environment.

The number of fish species that can be identified by the app will be limited to five out of the 20 dominant species in the fisheries management area 7 profile by BFAR/NFDRI 2020 report because the dataset will contain 5 species that will be collected from various sources such as BFAR, the internet, and own captured images from the market. These species are Buraw, Kuwaw, Sapsap, Turay, Tilapia, and Turingan. We limited them to 5 because of time constraints and the challenge of collecting the dataset because of certain factors. Firstly, there are limited datasets for some species out of the large number needed for each species to create an accurate model. Secondly, the challenge of keeping these species alive after being caught. Thus the underwater images will not be included in the dataset and the app will not be used in real-time detection and underwater.

Significance of the Study

The researchers aim to provide benefits of knowledge for the technology industry as well as the following: Fisheries Management Area 7 (FMA 7) will be able to identify the fish on its fishing grounds with the help of the findings, which will also provide the Bureau of Fisheries and Aquatic Resources (BFAR), particularly FMA 7, with additional current data, further. In a way that makes it easier to manage the resources brought by the bits of knowledge and concentrate on what can replenish the abundance of the ocean. The output data of the study will provide a scientific understanding that the organization may or may not know about the existing species of fish. By offering the ability to identify a species of fish, the developed software also helps the residents of coastal communities understand how to manage the resources in the area based on the fish species that have been recognized. The results of fish species identification can also give the local market a helpful fish market report, describing, for instance, what kinds of fish can be found in the market covered by FMA 7. The application's use can also assist nearby fishermen in correctly classifying the fish they have captured. To support this claim, based on the research of Villon et al. (2018), their team developed a CNN model that can identify a species of fish and compare it with human perception. The participants in the aforementioned study are experts in aquatic life. Researchers discovered that when compared to humans (89.3%), the CNN model had a higher correct recognition rate of 94.3 percent. And the results of the study will help future researchers, notably those working in the field of image processing, identify various species and better their understanding of how to develop the concept in a related area.

II REVIEW OF LITERATURES

This chapter explains the review of related literature and studies gathered from different references like the internet, books, online journals, and theses that are a great help in understanding this study. It provides a realization of the critical ideas, methods, and knowledge essential in fulfilling this study.

Related Literature

Fisheries Management Area

Fishing has been one of the top contributors in the Philippines' economy. According to the Bureau of Fisheries and Aquatic Resources the fishing industry's contribution to the country's Gross Domestic Product (GDP) is 1.52% at both current and constant 2018 prices. This translates to PhP 273.41 billion at current prices and PhP 266.22 billion at constant prices of the country's GDP of PhP 17,939 billion. In light of the significant contribution of this sector, Vannuccini et al. (2018) stated impacts of climate change may be linked to vulnerability in nations with a high reliance on fishing. Thus, it is necessary to increase the sustainability of fish and seafood production.

In order to promote sustainability, effective fisheries management must be implemented. In order to encourage the protection of living resources in the ocean, the UN (including the Food and Agriculture Organization) has offered a number of frameworks, principles, regimes, and recommendations. Furthermore, Fisheries management is not costless.

In contrast, Li (2022) stated that good fisheries management demands solid technological and financial support to collect, analyze, and allocate data, conduct scientific research, and effectively enforce the law (Li, 2022).

Monitoring the condition of specific fish populations on a regular basis is crucial to sustainable fisheries management. In South Korea, determining where fish stocks sit with respect to key limit or target reference points allows management performance to be evaluated. Fisheries and Aquaculture in Korea regularly assess the fish population. Particularly, the status of 18 stocks has recently been quantitatively assessed. Of these, 18 are assessed to have a biologically favorable status and meet additional management objectives.

Japan also established fisheries management policies.Yao et al.(2022) stated in their study that in 2021, the Japanese Fisheries Agency (JFA) released its latest fishery development plan and related promotion policies. For example, the agency plans to expand the scale of aquatic product aquaculture, strengthen the production and circulation of aquatic products, and improve preferential policies for individuals employed in outlying islands

Here in the Philippines, agencies also initiated a way in conservation of marine resources. To determine the proper scale of management, our Philippine seas are spatially divided into twelve Fisheries Management Areas, or FMAs.

Oceana Philippines Vice President Gloria Estenzo Ramos (2015) stated that "Sufficient data on fisheries is required for science-based decision making" She said that we live in a country that is heavily reliant on sea. "We need information about our marine resources and their use, as well as access to successfully create and implement policies that will protect our massively threatened marine environment"

According to the Bureau of Fisheries and Aquatic Resources, it is an approximation of an ecosystem scale of management. Managing fisheries at the FMA level allows for a more ecosystem based approach to fisheries management (EAFM) as it now considers the range and distribution of fish stocks based on an approximation of an ecosystem, rather than based on political or legal jurisdictions only. The LGU and BFAR will now work together to manage the fisheries in each FMA. Each FMA shall create reference points, adopt harvest control rules based on scientific data, and suggest the necessary harvest control measures through an FMA management board with assistance from a Scientific Advisory Group.

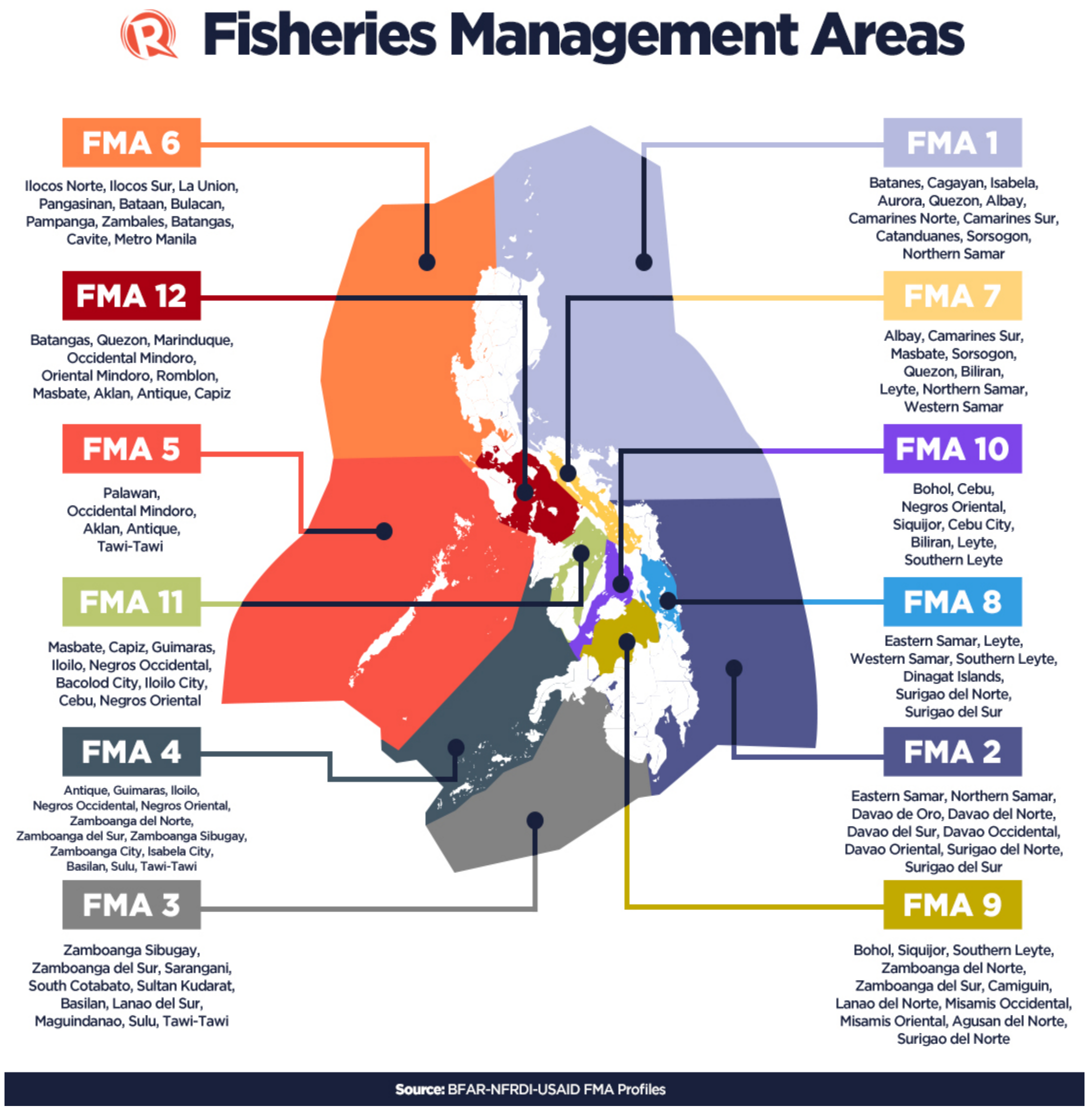


Figure 1: **Fisheries Management Areas**

Note: Fisheries Management Areas is reprinted from Get to know your fishes (Aug 24, 2021) Rappler

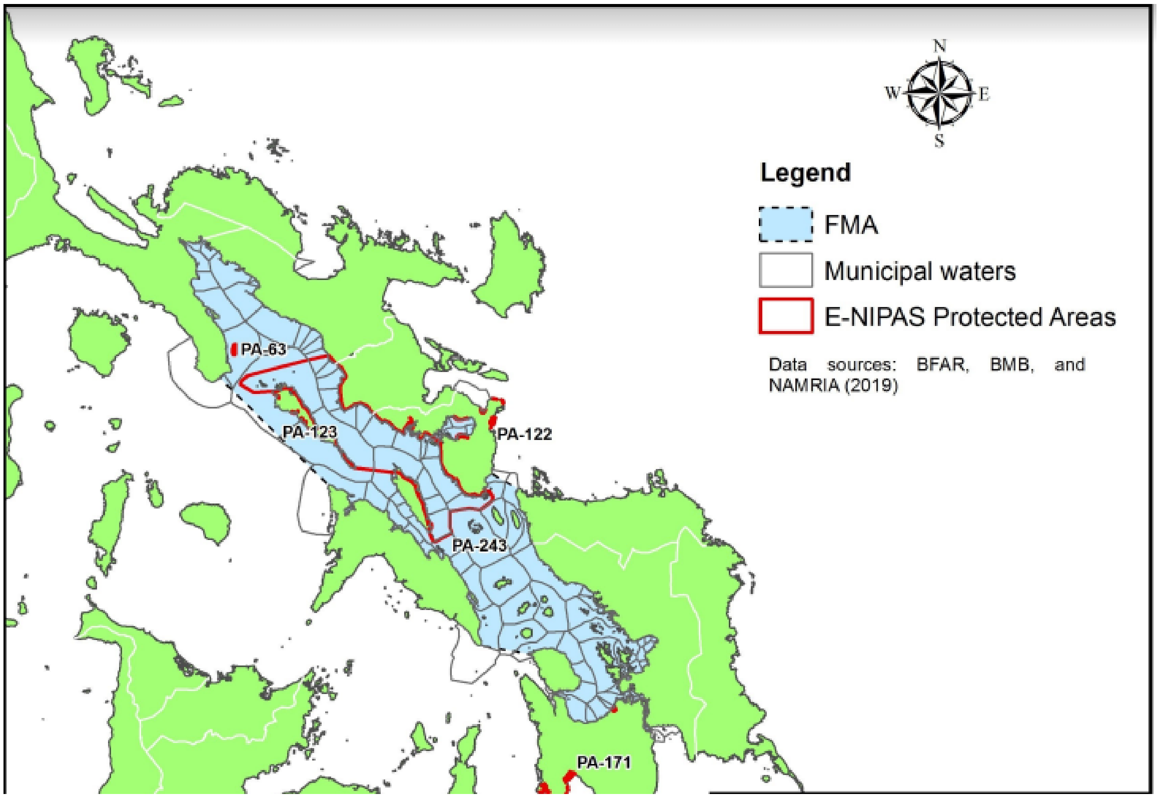


Figure 2: **FMA 7**

Note: FMA 7 is reprinted from Individual FMA Profile (July, 2020) BFAR

Fisheries Management Area (FMA) 7. FMA 7 covers Quezon Province, Camarines Sur, Albay, Sorsogon, Masbate, Northern Samar, Biliran, Leyte, and Western Samar. The regional composition includes Region 4A (Calabarzon), 5 and 8. In Region 4, Ragay Gulf is the key fishing ground. In Region 5, Sorsogon Bay, Burias Pass ,Ticao Pass, and Ragay Gulf are the major fishing areas. In Region 8, Samar Sea, Carigara Bay, Magueda Bay, San Bernardino Strait. and Irong-Irong Bay are the major fishing grounds.

Fish Identification

The shape of fish's heads, the location of their mouths, the type and location of their fins, and their average adult size are some traits that distinguish them apart. When combined with other characteristics like geographic range, color patterns like vertical stripes or fin patches may also aid in differentiating fish. (Ariganello et al., n.d.)

Ju & Xue (2020) stated that the protection of fish populations and fish culture depend heavily on a type of object identification technology called marine fish recognition. The fishing industry studies each fish species' distribution and modifies its fishing mechanisms for controlling.

Pudaruth et al. (2021) affirmed that the accurate identification of the fish species is essential to every study. Accurate identification is necessary for evaluating fish stocks, capture, and seafood labeling.

For the purpose of making choices about the management of natural resources, fish monitoring programs frequently gather, identify the species of the fish, and count the number of individual fish over time. Therefore, species misidentification can have a negative impact on the usefulness of the information used to support these judgments. (Kirsch et al., 2018)

Particularly, in the Field Guide to Coastal Fishes of Palawan by Benjamin Gonzales (2013) mentioned that the process of fish identification was based on images gathered in landing sites and laboratories.

Torres & Santos (2019) stressed that misidentification of species could endanger not only that particular species but also the ecosystem as a whole through ineffective monitoring procedures, inefficient resource allocation for conservation initiatives, and an unnoticed drop in fish populations.

Rum & Az (2021) proposed that minimizing human mistakes during the process of fish observation and analysis is crucial in fishery education and calls for an automatic system detection.

Fish Species

In the book Environmental Change and Agricultural Sustainability in the Mekong Delta by Stewart & Coclanis (2011), FishBase is described as a credible international information system that is available to the public, allowing countries to take advantage of global knowledge of local importance.

Another website called World Register of Marine Species (WoRMS) is intended to give a reliable and thorough list of names for marine creatures, together with information on synonymy. Other names in use are included so that this register can be used as a guide to understand taxonomic literature, even if valid names receive the highest attention.

The Field Guide to Coastal Fishes of Palawan by Benjamin Gonzales (2013) contains local names for the fishes.

The following information was gathered from FishBase, WoRMS, and Field Guide to Coastal Fishes of Palawan:

Island Mackerel *(Rastrelliger faughni)*

Kingdom	Animalia
Phylum	Chordata
Class	Actinopteri
Order	Perciformes
Family	Scombridae
Genus	Rastrelliger
Species	Rastrelliger faughni

Table 1: **Island Mackerel Taxonomic Hierarchy**

Local names for this fish includes: Alumahan bato, Island mackerel, Alumahan, Andohaw, Anduhan, Anduhaw, Bantala-an, Bulao-bulao, Burao, Buraw, Burirawan, Gutob, Hasa-hasa, Kabalyas, Kapisnon, Karabalyas, Lumahan, Panit, Tamarang

Description: The belly is a silvery yellow color. At the first dorsal fin's base, some specimens have two to six big spots and two faint stripes at the level of the lateral line. Gill rakers do not go all the way inside the mouth. Behind the base of the pectoral fin, there is a black spot. Swim bladder is present. Small and isolated inter pelvic processes are present. It has rudimentary anal spine and the longest gill raker has 30 to 55 bristles on one side.

Furthermore, this specie belongs to epipelagic and neritic species that are found in seas with a maximum surface temperature of 17°C. It feeds on the largest zooplankton species, completing the range of planktonic foods available to the other two species of Rastrelliger.

Red BigEye *(Priacanthus macracanthus)*

Kingdom	Animalia
Phylum	Chordata
Class	Actinopteri
Order	Eupercaria incertae sedis
Family	Priacanthidae
Genus	Priacanthus
Species	Priacanthus macracanthus

Table 2: **Red BigEye Taxonomic Hierarchy**

Local names for this fish includes: Kwahao; Bukawbukaw; kuwaw

Description: Red BigEye a relatively deep-bodied fish of medium size. It has large eyes and an oblique mouth with an upward-projecting lower jaw. The body narrows very slightly beneath the middle of the dorsal fin's soft section before abruptly ending at the peduncle.The dorsal and anal fin membranes of this species differ from those of *P. fitchi* by having a lot of rusty brown to yellowish dots, as well as by having a less tapered body. It occurs in reefs both on land and in sea, at depths ranging from 20 meters to 400 meters and reportedly highly common in the South China Sea and Andaman Sea, where it forms aggregations on open bottom areas. Red BigEye is being sold fresh and whole. During the day, they are also seen behind ledges or hovering nearby coral heads.

Splendid Ponyfish *(Leiognathus splendens)*

Kingdom	Animalia
Phylum	Chordata
Class	Teleostei
Order	Perciformes
Family	Leiognathidae
Genus	Leiognathus
Species	Leiognathus splendens

Table 3: **Splendid Ponyfish Taxonomic Hierarchy**

Local names for this fish includes: Sapsap; Tapsay

Description: This species can be identified by its lack of cheek scales, practically full anterior dorsolateral body scaling, lack of a semicircular bare patch on the neck, and smooth or weakly serrated lower preopercular ridge margin. There are no scales in the pelvic keels' interspace, strong second spines on the dorsal and anal fins, and a jet-black spot on the spinous dorsal fin.The coastal waters are home to this schooling species. It consumes bivalves, foraminiferans, crustaceans, and fish.

Fringescale Sardinella *(Sardinella fimbriata)*

Kingdom	Animalia
Phylum	Chordata
Class	Actinopteri
Order	Clupeiformes
Family	Clupeidae
Genus	Sardinella
Species	Sardinella fimbriata

Table 4: **Fringescale Sardinella Taxonomic Hierarchy**

Local names for this fish includes: Tamban-tuloy, Turay

Description: The body slightly compressed yet varied. It has 29 to 33 scutes overall. Vertical striae on scales do not meet in the center, and the rear half of the scales have a few perforations. There is a dark patch at the origin of the dorsal fin. In coastal waters, it forms schools. Misidentifications (particularly of *S. gibbosa* in Indian waters and *S. albella* in the western Indian Ocean) render published biological data potentially inaccurate. It is sold fresh, dried-salted, cooked, or formed into fish balls.

Bullet Tuna *(Auxis rochei)*

Kingdom	Animalia
Phylum	Chordata
Class	Actinopteri
Order	Scombriformes

Family	Scombridae
Genus	Auxis
Species	Auxis rochei

Table 5: **Bullet TunaTaxonomic Hierarchy**

Local names for this fish includes: Tulingan, Turingan

Description: The back is bluish, but the head is deep purple or practically black. It has an area with no scale and a pattern of 15 or more rather broad, nearly vertical dark bars. This species has white belly, pectoral and pelvic fins are purple, and their inner sides are black. The body is robust, elongated and rounded. Meanwhile, teeth are small and conical, in a single series. Adults are primarily captured near islands and in coastal seas.It form schools. Moreover, they feed on small fish, notably anchovies, as well as squid, crab, and other crustacean larvae. Larvae and eggs are pelagic. They are regarded as a crucial component of the food web due to their abundance, especially when used as forage for other species of commercial significance. Also captured with troll lines and encircling nets. This fish is marketed Fresh, frozen, dried, salted, smoked, and canned.

Image Processing

Lewis (2020) defined image processing as the manipulation of images to be processed and produce the desired output. The image processing approach can be performed using image acquisition, image pre-processing and image analysis. In another study, Apoloni et al (2022) emphasized that image processing is the utilization of a computer to process digital images through an algorithm.

Birchfield (2018) elaborated that image processing is a research area that involves using operations on pictures. Images used as input are output together with any actions that were performed on them. On the other hand, the study of applying algorithms to comprehend images is known as image analysis. Its output could not be visual at all. In addition, Xu (2021) viewed image processing technology as the methods and means of image denoising, correction, segmentation, feature extraction and so on.

Meanwhile, in the paper of Joshi (2018), image processing is described as the field of information technology (IT) that involves manipulating images to highlight or underline specific details. For improved processing, several variances and distortions are taken into consideration. This makes it possible to utilize it for additional tasks like information extraction that isn't related to images. The elements of digital image processing are the image capture, storage, processing, and display.

Image processing is already being used for fish identification. Zhang et al., (2022) emphasized that fish picture input, fish feature selection, classifier construction, classification, and recognition are the fundamental steps in fish image recognition. Early techniques overly focus on artificial selection characteristics, which primarily rely on expert previous knowledge, to recognize fish using attributes like contour, form, and color. But deep learning has flourished in the field of computer vision. The deep learning-based approach is progressively displacing the conventional machine learning approach. Deep learning has hundreds of parameters and can automatically learn how to represent characteristics from enormous data.

Background subtraction (BS) method is a rapid method of localizing objects in motion from a video captured by a stationary camera. This forms the primary step of a multi-stage vision system. This type of process separates out background from the foreground object in sequence in images (Chandan et al., 2018).

Object tracking is done in video sequences like security cameras and CCTV surveillance feed; the objective is to track the path followed, speed of an object.

The rate of real time detection can be increased by employing object tracking and running classification in few frames captured in a fixed interval of time (Chandan et al., 2018)

Image Processing on Smartphones

A smartphone nowadays is a reasonably priced hand-held computer with a high processing capacity. These gadgets are also useful for numerous jobs in farming and agriculture because of the incorporation of built-in high resolution sensors and cameras(Cubero et al., 2018). The study of Valdoria et al. (2019)

utilized the android smartphones in the implementation of the mobile application called iDahon that detects the plant diseases.

Marine scientist Dr. Stephen Box (2015), presented a fisheries mobile application and stated that the application can privide the wealth of data "which will be collected using these tools will greatly contribute to data analysis, and can be a primary basis for any plans related to fisheries management and sustainability"

OpenCV library is the best approach to use computer vision on Android Devices. OpenCV uses the front camera of the android devices to capture the image and further frame pre-processing gesture extraction and assimilation is done by device (Joshi et al., 2015).

OpenCV or Open Computer Vision is an Application Programming Interface (API) Library that is used in digital image processing. OpenCV Library can obtain higher performance than the self-made algorithm built in Android Library (Agus Suryawibawa et al., 2015).

OpenCV has its own Java API (Application Program Interface) (Hellman, 2013), and on the implementation study of Sharma et al. (2017) elaborated that it doesn't depend on Java-based Android Camera API.

The OpenCV library was officially introduced in 1999 by Intel Research initiative to advance CPU-intensive applications. The OpenCV library in the earlier version written in C, However since version 2.0, OpenCV includes both C interface and C++ interface. Starting version 2.2, OpenCV can be built for Android OS (Ammar et al., 2012).

Real time image processing can be achieved using the OpenCV library. In the study, Sharma et al. (2017) employed OpenCV library to recognize air-swipe hand gestures through android cameras.

CNN

An Artificial Neural Network is an information processing technique. It works like the way the human brain processes information. ANN includes a large number of connected processing units that work together to process information. They also generate meaningful results from it (Sharma, 2017).

In the study of Lee et. al (2018) stated that CNN is a subclass of Artificial Neural Network (ANN). In another study by Alzubaidi et al. (2021) said that CNN's key benefit over its predecessors is that it automatically recognizes the significant characteristics without any human supervision, making it the most popular.

Convolutional neural networks have demonstrated excellent achievement in problems of computer vision, especially in image classification (Sultana et al., 2019). In the same study, they stated CNN as a special type of multi-layer neural network inspired by the mechanism of the optical system of living creatures. The structure of CNNs was inspired by neurons in human and animal brains, similar to a conventional neural network. More specifically, in a cat’s brain, a complex sequence of cells forms the visual cortex; this sequence is simulated by the CNN (Alzubaidi et al., 2021).

As a bio-inspired neural network, the Convolutional Neural Network (CNNs) has become the most successful deep learning model in the computer vision industry (Lee et al., 2018).

AlexNet

Wei, (2019) in their study, stated that AlexNet is a CNN architecture that consists of eight layers: five convolutional layers and three fully-connected layers. The architecture contains new features such as ReLU nonlinearity, Multiple GPUs, and Overlapping pooling which made this model capable of achieving high accuracies on very challenging datasets.

Swathi et al. (2020) defined convolutional layer as the one which performs a series of convolutional operations on its inputs to facilitate pattern recognition.

The AlexNet contains 8 layers with weights; 5 convolutional layers and 3 fully connected layers. At the end of each layer, ReLu activation is performed except for the last one (Pujara, 2021). It is also stated that the use of (Rectified Linear Unit) Nonlinearity is an important feature of AlexNet as it allows deep CNNs to be trained much faster compared to employing saturating functions like tanh or sigmoid.

According to another study, Convolutional layers apply a convolution operation to the input, which reduces the number of parameters of the problem, to allow deep layers with fewer parameters. In fully connected layers, every neuron in one layer is connected to every neuron in another layer. As a result of this eight-layer architecture, there are 60 million parameters. Second, AlexNet used graphics processing units (GPUs) to train the model. GPUs are essentially parallel floating-point calculators, which are much faster than conventional central processing units (CPUs). Using GPUs meant they could train larger models, which led to lower error rates. Finally, they used the non-saturating rectified linear activation unit (ReLU) activation function, which had reduced overfitting and improved training performance over other activation functions such as tanh and sigmoid (Xiao, 2019).

Studies showed that AlexNet CNN architecture can be used in real-time using frames taken from the camera or using OpenCV framework. First, the study of Solovyov & Pastuhov (2018) titled “Wildfire smoke detection using convolutional neural networks” used the Alexnet model as a CNN architecture, OpenCV as framework for image processing and object detection and Java as a programming language. In another study Liu et al. (2021) also used AlexNet architecture with OpenCV framework to achieve real-time pedestrian detection.

Related Studies

The identification and naming of fish species in underwater imagery processing has been in high demand according to Kottursamy (2021).

The research conducted provides a solution to underwater image detection techniques by using an appended transmission map, refinement method and deep learning approach. Features are deeply extracted by multi-scale CNN for attaining higher accuracy in detecting fish features from the input images with the help of segmentation process.

Underwater videos have recently piqued the interest of marine ecologists to the study of fish populations. This technique produces a large amount of visual data and does not affect fish behavior. Research of Ben Tamou et al. (2018) used Convolutional Neural Network AlexNet with transfer learning for automatic fish species classification. Features are extracted from foreground fish images of the available underwater dataset using the pretrained AlexNet network either with or without fine-tuning. For classification, linear SVM classifier is used. The experiment achieved a 99.45% that demonstrates the effectiveness of the proposed approach on the Fish Recognition Ground-Truth dataset.

With regards to image processing, in the proposed approach of Parab et al. (2020) they classified RBCs using image processing and convolution neural networks (CNN). The incoming images are first pre-processed and segmented before the researchers can extract individual RBC images. RBCs were grouped in the study based on their exterior appearance, size, and shape. The researchers acquired 98.5% accuracy when compared to pathology lab reports. Allken et al. (2019) states that examining images from known positions in the trawl track provides high resolution ground truth for the presence of species. Therefore, they develop and deploy a deep learning neural network to automate the classification of species present in images from the Deep Vision trawl camera system. Chouiten (n.d.) automate fish recognition application running on a case protected smartphone and allowing the user to identify the fish by using the camera of the smartphone. The study focuses on the use of the CAMshift algorithm as well as Fish Analyzer. And in a study conducted by Sta. Ana K. et al. in 2021, created a program that will categorize the fruit's freshness using image processing and machine learning techniques.

Notably, the research by Villon et al. (2018) creates a CNN model that can identify a species of fish and compares human experience with CNN models or deep learning-based methods. The researchers produced 4 models using the CNN Convolutional Neural Network. The GoPro Hero3+ and Hero4+ cameras were used to record footage of fish that needed to be classified at a frame rate of 30 over 50 reef sites. Slow motion/5 frames per second were used to extract the images needed for the study from the video, and each was then captured as an image. The 450,000 pictures that the researchers were able to extract from the video contain 20 species that need to be recognized. 44,625 of the 450,000 filtered photos were used as the training data set. Four distinct data sets are produced during the study, and each one was utilized to train a different model. Then, these models are put side by side. The performance of the best CNN model out of the four was compared to how well humans can identify a fish's species. These experts in aquatic life are those who are asked to participate in the study. But first, the researchers trained the best CNN model using 900,000 images of complete and incomplete fish bodies, as well as the surrounding area. The researchers found that the best CNN model had a significantly higher correct identification rate (94.3%) compared to people (89.3%). The system not only performs better than humans at accurately identifying fish, but it can also see fish that are hidden by corals or other fish. In contrast to humans, the model may be able to distinguish blurry images and even little fish. As a result, the researchers of the study were able to identify fish from images of water with greater accuracy and sophistication than a human expert.

Fish species recognition is an important task to preserve ecosystems, feed humans, and tourism. According to Dos Santos et al. (2019) the new Convolutional Neural Network is composed of three branches that classify the fish species, family, and order with the aim of improving the recognition of species with similar characteristics. The method used gained an accuracy of 0.938 and 0.96, respectively compared to the traditional CNN recognition that obtained a lower accuracy level.

Additionally, Dhruv Rathi et al. (2017) applied Convolutional Neural Networks with Deep Learning approach for the study that processed and handled the massive dataset obtained from Fish4Knowlegde for evaluating the algorithm that categorizes fish species. ReLU 96.29%, tanh 72.622%, and Softmax 61.91% accuracy was obtained using the approaches. Overall, the study's accuracy couldn't reach 100% since certain photographs' background noise prevented them from being identified. Significantly, researchers Tseng et al. (2020) used deep Convolutional Neural Networks for their research on counting harvested fish and determining the type of fish in footage from electronic monitoring systems. The total accuracy of the fish type identification was 98.06% for TP fish. Accordingly, the remaining difficulties include species identification and improved fish counts.

Zhang et al. (2019) stated that the novel three-channel convolutional neural networks (TCCNN) model is constructed by combining three color components for vegetable leaf disease recognition. TCCNN model is suggested as a viable option for identifying vegetable leaf diseases by integrating three separate color components of the diseased leaf image including four convolution layers (C1, C2, C3, C4), three pooling layers (P1, P2, P3), and two fully-connected layers (FC1, FC2).

Furthermore, an analogous study was conducted by Rum et al. (2021), whose goal was to create the mobile application FishDetTec using Android Studio as the platform. The data were divided into two groups by the researchers: training data and testing data. The platform they utilized to create the Android mobile application was Android Studio. The computer programming language used was Python. For eight different fish species, 200 photographs were used in the study. The photographs were afterward processed by CNN for fish image identification while the researchers filtered them using data augmentation. To create the model, the researchers employed Tensorflow and Keras. With a training loss of 0.0125 and a validation loss of 0.25, the study had an accuracy rate of 87%. Still, the study performed moderately better than the early studies. According to the study of Pudaruth et. al, (2021) thresholding operation was performed on the images to subtract the fish from the background. Classifiers such as kNN, Support Vector Machines, neural networks, decision trees and random forest were used to find the best performing one. KNN achieved the highest accuracy of 96% together with another model for recognition, the TensorFlow framework, which produced a much higher accuracy rate of 98%. Additionally, Aji et al. (2020) proposed research to create an Android-based mobile learning media package for physics that is reliable and practical to use in education. The Android Studio 3.2 IDE at the minimal level of API 14 Ice Cream Sandwich was used by the researchers to create the application. As a result, the application is considered acceptable with a score of 84 under the Very Good standard, according to expert validator ratings.

As our study focuses on using the AlexNet Convolutional Neural Network for image processing, some researchers also used the AlexNet model for their study. In particular, the study by Minhas et al. (2019), the data was trained to classify the shots into long, medium, close-up, and out-of-the-field shots using the AlexNet Convolutional Neural Network. The results show that AlexNet or the researchers' model achieves the maximum accuracy of 94.07% when compared to other models such as Support Vector Machine (SVM), Extreme Learning Machine (ELM), K-Nearest Neighbors ((KNN), and standard Convolutional Neural Network (CNN)). In addition, the study of Ju (2020) provides a method to obtain more accurate and efficient accuracy results compared to an old AlexNet Model. According to him, traditional machine learning algorithms are incapable of recognizing images with complex backgrounds and various illuminations. These fish algorithms are based on factors of color, texture, and feature extraction, which results in low recognition accuracy or inferior robustness. Therefore, the improved AlexNet Model is used to achieve higher accuracy and less computational complexity compared to many state-of-the-art fish recognition algorithms.

Similarly, researchers Omonigho et al. (2020) also employed a modified AlexNet model for picture classification and image extraction during training (2020). The last three layers of the AlexNet model were removed and replaced with a fully connected layer (FC), a soft-max layer, and a classification layer by the researchers. The Mammographic Image Analysis Society (MIAS) database serves as the source of image data for the researchers. The mammography images were divided into two classifications, benign (normal) and malignant (abnormal) tumors, using a modified version of AlexNet. To reduce image noise during pre-processing, the researchers used a gaussian filter. Additionally, augmentation was used to increase the amount of data required. 31% of the data were training sets, while 69% were testing sets. These images are enhanced in order to do feature segmentation; after processing, the enhanced images are given to a customized AlexNet CNN model. Overall categorization accuracy is determined by the researchers to be 95.70%.

According to Yuan et al. (2016) Convolutional Neural Network is a hot research topic in image recognition. Latest shows that the Deep CNN model is effective at extracting features and representing images. In this paper, this capability is applied to image retrieval. The Caffe framework and the AlexNet model were used to extract image feature information. In the experiment conducted, use of two public image datasets, Inria Holidays and Oxford Buildings, to look for the influence of different datasets. The results demonstrated that the Deep CNN model's fusion feature can improve image retrieval results and that different weights should be used for different datasets.

According to the study of Llaneta et al. (2022) to determine the sweetness of Watermelon through its shape, texture, color, and field spot use of Image Processing and Machine Learning must take place. Sweet 18 F1 and Sugar Baby Max F1 images were obtained and labeled based on the results of a Brix test performed with a sugar refractometer. There was pre-processing and feature extraction performed. The accuracy, precision, recall, and f-1 score evaluation metrics of the One-Class Support Vector Machine (OCSVM) and K-Nearest Neighbor Algorithm (KNN) models were used.

The study of Fu’adah et al. (2021) proposes the Convolutional Neural Network (CNN) using AlexNet architecture as a method to develop an automated classification system of Alzheimer’s disease based on digital image processing. Each layer of CNN learns to detect a variety of images. Image processing is applied to process images at a different resolution, and the output of each image is processed and used as input to the next layer. Datasets utilized are the Magnetic Resonance Image Datasets of Alzheimer collected by Sarvesh Dubey.

Similarly, researchers Kumar et al. (2021) proposed a study that uses the AlexNet model to identify Alzheimer's at the MCI level. AlexNet's utilization of the entire human brain results in 98.35% accuracy.

The study of Davari et al. (2021) focuses on deep learning-based methods for defect detection and classification of power distribution lines using video analysis. Davari et al. used AlexNet or GoogleNet to determine the equipment type and the severity level of defect is determined. The first stage is dataset preparation, which involves recording different videos from distribution lines with a CoroCam 6D2 camera and labeling them based on the defect type and severity level. The process is then carried out in such a way that only a limited number of frames are used for processing, and power devices are detected in each frame using Faster R-CNN. The proposed method not only surpasses the state-of-the-art, but it is also a practical method that can automatically identify defects in distribution lines, even in videos containing multiple potentially defective devices, with the least reliance on environmental conditions.

Ling Zhu et al. (2018) research paper entitled “High performance vegetable classification from image based on AlexNet deep learning model ”, proposed a high performance method for vegetable images classification based on deep learning framework. The AlexNet network model in Caffe was used to train the vegetable image data set. The vegetable image data set was obtained from ImageNet and divided into training data set and test data set. The output function of the AlexNet network adopted the Rectified Linear Units (ReLU) instead of the traditional sigmoid function and the tanh function, which can speed up the training of the deep learning network. The experimental results showed that when the AlexNet network model was used to train a different number of vegetable image data sets, the classification accuracy decreased as the number of data sets decreased. The experimental verification revealed that the deep learning method achieved an accuracy rate of 92.1% in the test data set, which was significantly higher than the BP neural network (78%) and SVM classifier (80.5%) methods.

Additionally, Azore et al (2022) which categorizes banana varieties in the Philippines employed photos that were similarly taken from films and exported as image sequences at a rate of five frames per second. For the CNN model development, they also used Python with the TensorFlow and Keras packages. The researchers' primary programming language of choice for creating the Android application was Java. For the expanded version of the dataset, the researchers pre-processed the image by cropping, scaling, rotating, and sorting. To develop a balanced version, the researchers deleted several photos due to their similarities. Convolutional neural networks were also built by the researchers and utilized to train the model. Overall, the trained research model performed satisfactorily and extracted pertinent characteristics from the seven banana types. However, only bananas that appeared to be typical in appearance were successfully identified using ImageNet. Moreover, milkfish, round scad, and tilapia are the three fish that Filipinos consume the most, and Navotas, et al. (2018) created an android application that automatically recognizes these fish as well as their freshness. Android Studio was used to make the application's image processing possible. As a result, the researchers used Android Studio, MATLAB, C++, and OpenCV to create the software. The images were taken with the phone's camera. The eyes, gills, and skin are the three components that will be examined in this research. The section was removed by the researchers using OpenCV code and RGB values. Researchers set the RGB values as the input for the Neural Network that will output the freshness level (1 - stale, 5 - fresh). The classification of the fish and its level of freshness can be determined by the study.

Synthesis

The study used AlexNet, an eight-layer CNN architecture that Wei (2019) described as an improved design capable of achieving high accuracy on exceedingly challenging datasets, in addition to the aforementioned findings. There has also been a significant demand for fish species identification and naming in picture processing, as Kottursamy (2021) pointed out. As a result, the studies mentioned above are used to classify a few fish that are found around the FMA 7 site. Based on the available research, it is a common practice to construct a small number of applications focusing on fish identification while merely developing models. Research on fish identification applications has been rare locally, notably in the province of the Philippines called Albay. As a response, the researchers develop a community-use application for fish identification.

Conceptual Framework of the Study

The key steps of the study are depicted in the illustration below. This covers the input, process, and output. The images of fishes found in FMA 7 will serve as the input to be used for training and testing. Additionally, relevant information on the different fish species will be acquired. The data will be divided into training and testing datasets. After the data gathering, the images will undergo preprocessing. Then, the CNN model will be constructed and will be trained using the preprocessed images.

After the training process, the model will be tested to determine accuracy. Once the training produces satisfactory results, the final model will be embedded into an Android application. This application will serve as the output of the study.

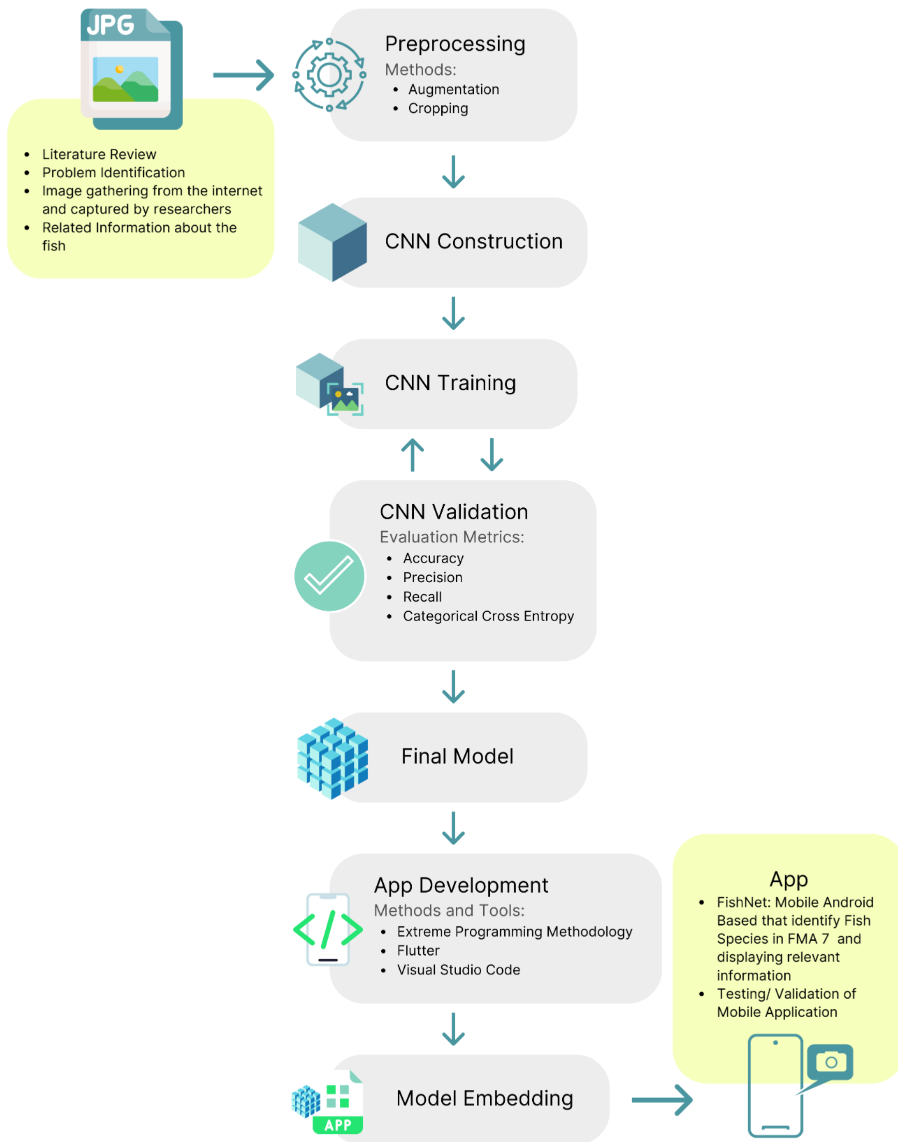


Figure 3: **Conceptual Paradigm**

Definition of Terms

The following terms are explained further, either conceptually or operationally:

AlexNet Model Architecture. The first convolutional network to employ a GPU to improve performance. AlexNet supports multi-GPU training by distributing the model's neurons between two GPUs, with half of the neurons being placed on one GPU. This not only allows for the training of a larger model but also shortens the training period.

Convolutional Neural Network (CNN). CNNs are mostly applied for image recognition and classification. CNN's capacity to do convolutions is its expertise. The potential for further uses of CNNs is limitless and needs to be explored and pushed to further boundaries to discover all that can be achieved by this complex machinery.

Fisheries Management Area 7. Members of the Fisheries Management Area's Management Body are tasked with developing management plans that are grounded in research and assessing advice from the Scientific Advisory Group and important stakeholder engagements. FMA 7 is composed of Quezon Province, Camarines Sur, Albay, Sorsogon, Masbate, Northern Samar, Biliran, Leyte, and Western Samar.

Image Processing. Image processing is the conversion of a physical image into a digital format and applying various operations to it in order to create certain models or extract information from the image.

III OPERATIONAL FRAMEWORK

This chapter describes the research methodology that will be utilized by the researchers. The data collection, model training, and other project requirements will also be expounded. Furthermore, the software development process will be discussed in detail.

Materials Needed

Hardware

As the study needs a computer system such as the hardware to perform the task the researchers are going to use the provided tools with their device specification. The model will be constructed using the ASUS TUF gaming F15 during the coding, testing, and overall process phases. The Android phone Infinix NOTE 12 with Android version 12 will be used to deploy the FishNet application for testing.

Laptop	Processor	Intel® Core™ i5-10300H CPU @ 2.50GHz 2.50GHz
	Installed RAM	8.00 GB (7.84 GB usable)
	System Type	64-bit operating system, x64-based processor
Android Cellphone	Model	Infinix X670
	Processor	Helio G96
	Installed RAM	8.00 GB + 3.00GB

	Android Version	12
	Front Camera	16M
	Rear Camera	50M TRIPLE Camera

Table 6: **Hardware Specification**

Software

A set of instructions, data, or programs used to operate computers and carry out specific tasks is referred to as software. To ensure compatibility, software used had specific version requirements. These versions are the latest according to their websites. CNN will be developed and trained using the Windows 10 operating system, as well as an Android application. Android is the target operating system for deployment. Tensorflow and Python are the chosen programming languages to be used. Tensorflow platform aids in the implementation of best practices for data automation, model tracking, performance monitoring, and model retraining. Keras allows users to productize deep models on smartphones (iOS and Android), on the web, or on the Java Virtual Machine. Spyder is a Python-based integrated development environment (IDE) that is open-source and cross-platform. By utilizing the capability of GPUs for the parallelizable portion of the calculation, CUDA enables developers to accelerate computationally heavy applications. CUDA Deep Neural Network (cuDNN) is a GPU-accelerated library of primitives for deep neural networks. It provides highly tuned implementations of routines arising frequently in DNN applications. OpenCV (Open Source Computer Vision Library) is a free and open source software library for computer vision and machine learning. OpenCV was created to provide a common infrastructure for computer vision applications and to speed up the incorporation of machine perception into commercial products. Flutter is written into Dart Language used for crafting beautiful, natively compiled applications for mobile, web, and desktop from a single codebase. Flutter works with existing code. Keras, Spyder, CUDA, cuDNN, OpenCV, Flutter and Dart are some of the software to be used during the development, coding, training and the overall process.

Software Used	Software Version
Windows 10 (OS for Training)	21H2
Android (Target OS)	12.0
Tensorflow	2.10.0
Python	3.9.12
Keras	2.10.0
Spyder	5.1.5
CUDA	11.8
cuDNN	8.3
OpenCV	4.6.0
Visual Studio	17. 3
Flutter	2.8.0
Dart	2.15.0
PyCharm Community	2022.3

Table 7: **Software Specification**

Research Methodology

This study utilizes the Developmental Research Design using Rapid Application Development Methodology. Developmental Research Design has been defined as the systematic study of designing, developing, and evaluating instructional programs, processes, and products that must meet internal consistency and effectiveness criteria. One of the most significant Agile techniques for software development is Rapid Application Development Methodology (RAD) that emphasizes continuous iterations and prototypes based on user feedback. It enables users to incorporate updates based on usage rather than a strict development schedule.

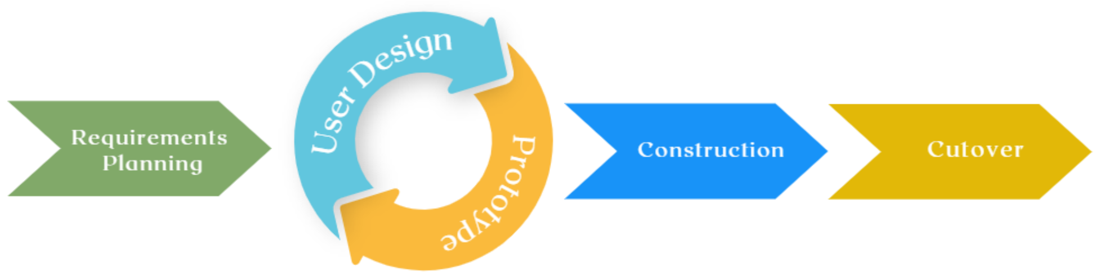


Figure 4: **Rapid Application Development Model**

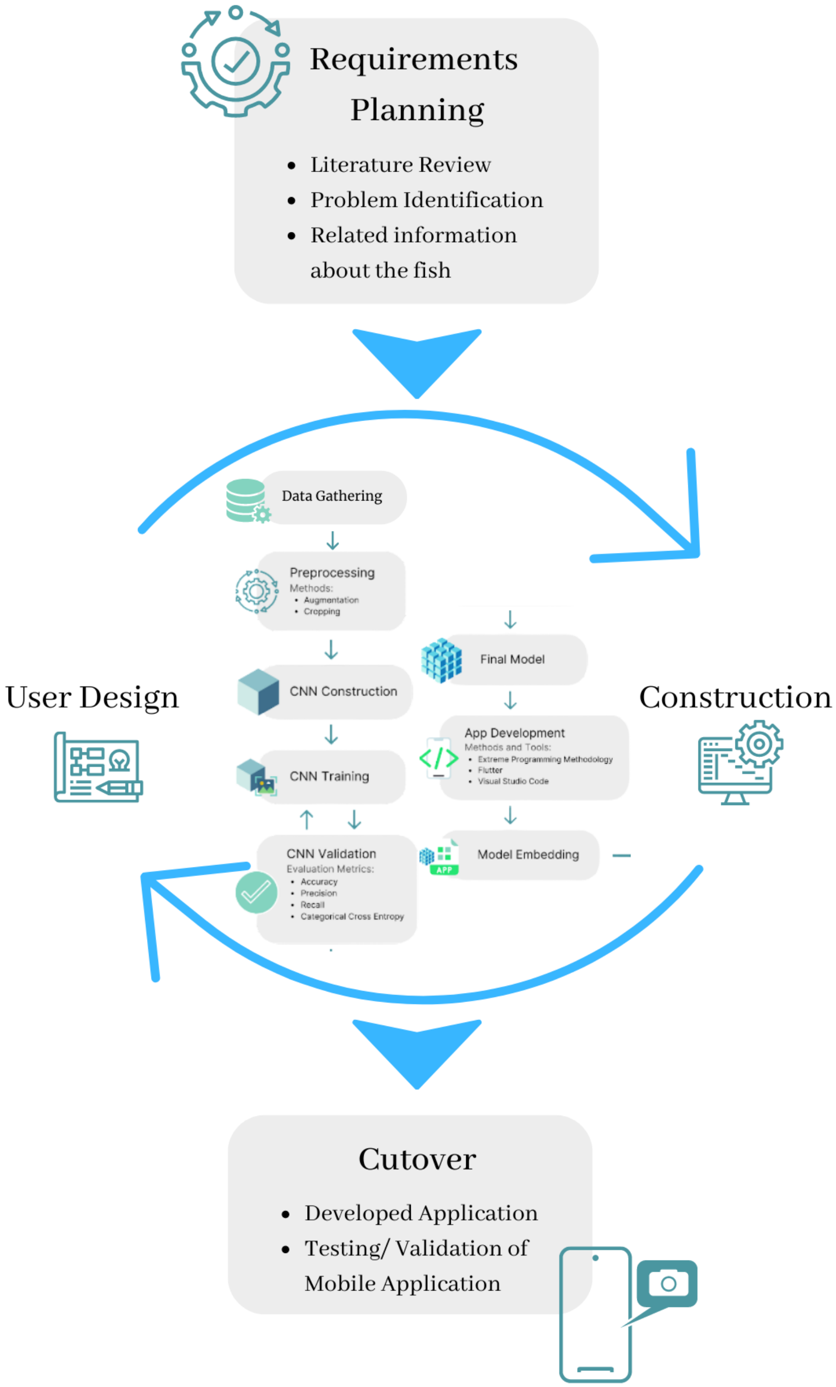


Figure 5: **Rapid Application Development Flowchart**

Phase 1: Requirements Planning

This phase aims to address the general objective of the study. Brainstorming became the primary step in formulating the flow of this research. Random ideas are tackled in order to create a product that will greatly benefit people. Weekly meetings were held to discuss the details of the study and its implications.

In conducting this research, a Gantt Chart is created to complete tasks within a specific time frame. Through this, researchers will be pushed through to complete all needed tasks before the allotted time duration. Tasks were sub-divided accordingly, using a Spin the Wheel Application. Researchers formulated the Rapid Application Development methodology best suits in developing this study.

Data gathering procedure will be conducted through collecting images from the Bureau of Fisheries and Aquatic Resources Provincial Office and from self captured pictures of fishes by researchers.

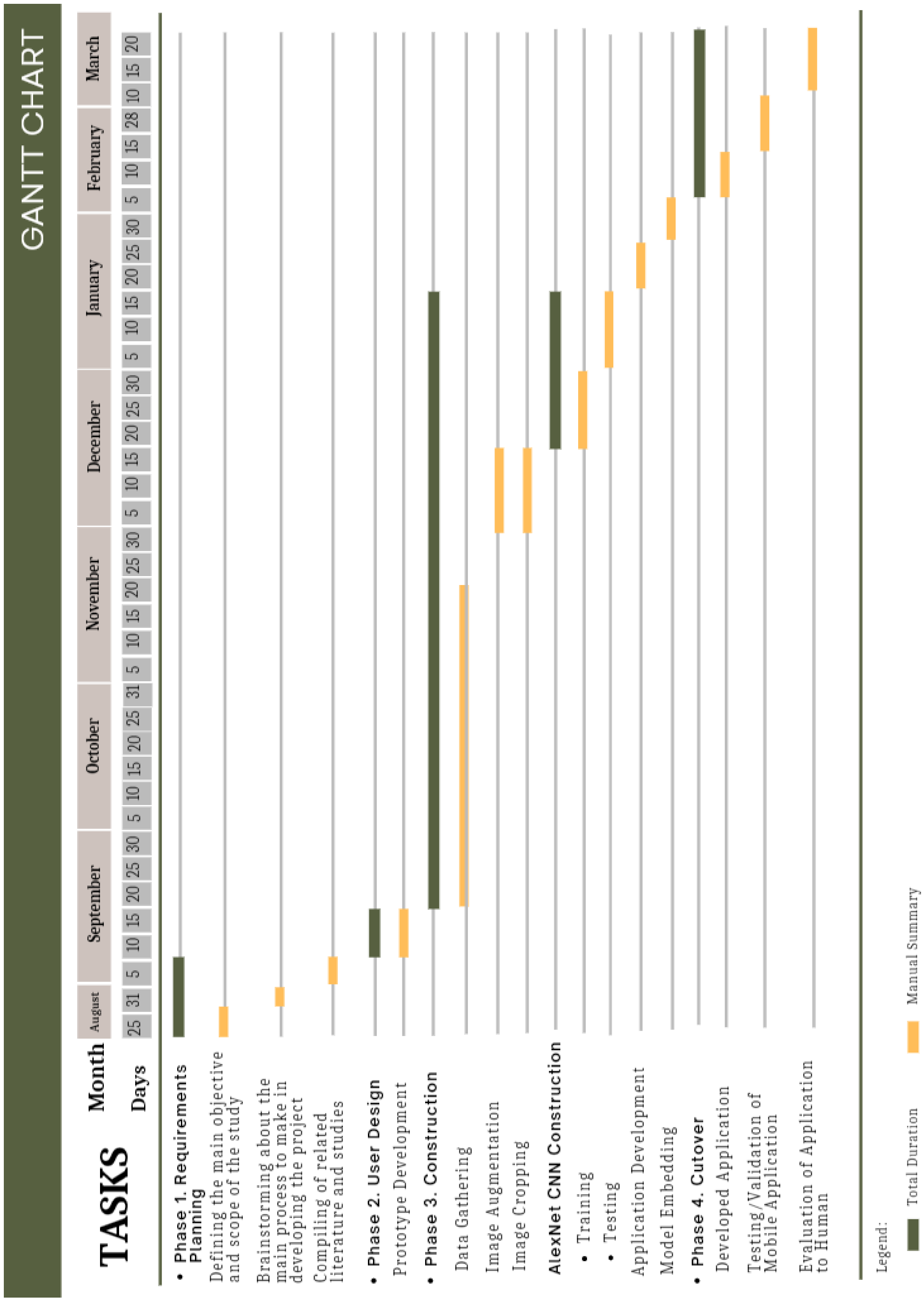


Figure 6: **Gantt Chart**

Phase 2: User Design

This phase involves developing a prototype for the proposed application. The user interface will be developed using Figma, which is a graphics editor. The main interfaces will include Home interface, Results interface, and Identification interface. The prototype to be developed will identify if it is a fish or not. If it is a fish under the scope of the study, it will show related information.

FISHNET

Fish detection for FMA 7

Figure 7: **Flash Screen**

Upon opening the mobile application, the flash screen will pop up. The flash screen includes the map of FMA 7, app name, and simple description.

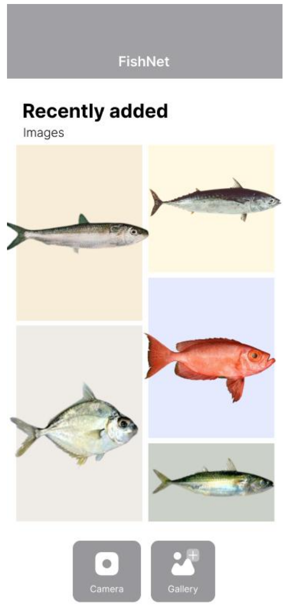


Figure 8: **Home Interface**

The Home interface will include buttons for capturing an image and accessing image from the gallery. Recently captured photos will also appear in homepage.

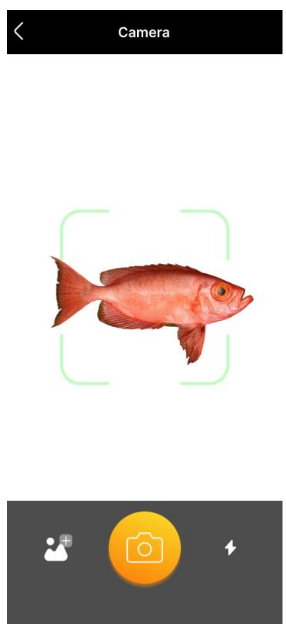


Figure 9: **Identification Interface**

Meanwhile, the Identification interface will access the phone camera and pop up a square where the fish being identified will fit.

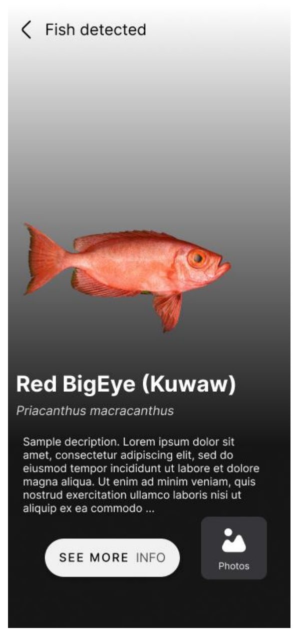


Figure 10: **Results Interface**

The Results interface will include the local and scientific name, descriptions, and related images of the identified fish.

Phase 3: Construction

This phase merges the beta and prototype systems from the design phase to produce a functional model. Data gathering, coding, program and application development, unit, integration, and system testing are all included in the preparation for rapid building. The CNN AlexNet architecture will be used to construct the model. The convolutional layer built within the CNN decreases the high dimensionality of the images. The AlexNet architecture has 650,000 processing neurons and 60 million parameters, with three fully linked layers and five convolutional layers. To yield positive results, it also involves ReLU and Dropouts.

3.1 Data Gathering

The researcher aims to gather the images in three methods for data gathering. The researchers will initially obtain photographs from the internet, followed by images researchers have taken themselves, and then, upon request, the dataset from Fisheries Management Area 7. These data will then be used to train and test the model.

3.2 Preprocessing/ Augmentation

The image of a fish will initially go through image augmentation. The researchers employ image augmentation to create new examples from the existing image since the study required a significant amount of data for the training set. These will provide the researchers with the precise amount of data needed for the algorithm to produce accurate results. To create a 256x256 image that can be fed to the AlexNet, data will be scaled and resized. The image will be resized to 256x256 and converted to RGB. The image must be this size in order to be used by the researchers for training the model, Figure 3 shows the network structure of the AlexNet.

3.3 Training model

The AlexNet architecture will receive the fish images after the preprocessing. The fish image will be processed using AlexNet's eight layers, which include three fully connected layers and five convolutional layers. The features from the fish image that need to be processed are extracted by the filters in each layer. The AlexNet process flow is shown in Figure 3. A convolutional layer with 96 11x11x3 kernels makes up the first layer of the AlexNet, which is followed by an Overlapping Max Pooling layer. Another Conv and Max Pooling follows. The third with 384 kernels, fourth with 384 kernels, and fifth with 256 kernels, these are convolutional layers that are connected. After the fifth convolutional layer comes the Overlapping Max Pooling layer. The Overlapping Max Pooling layer, whose output is fed into a series of two fully connected layers. After the convolution and fully connected layers, the second fully connected layer feeds the image to a softmax classifier with 5 class labels. ReLU nonlinearity is used along with the process, allowing the CNN model to be trained considerably more quickly.

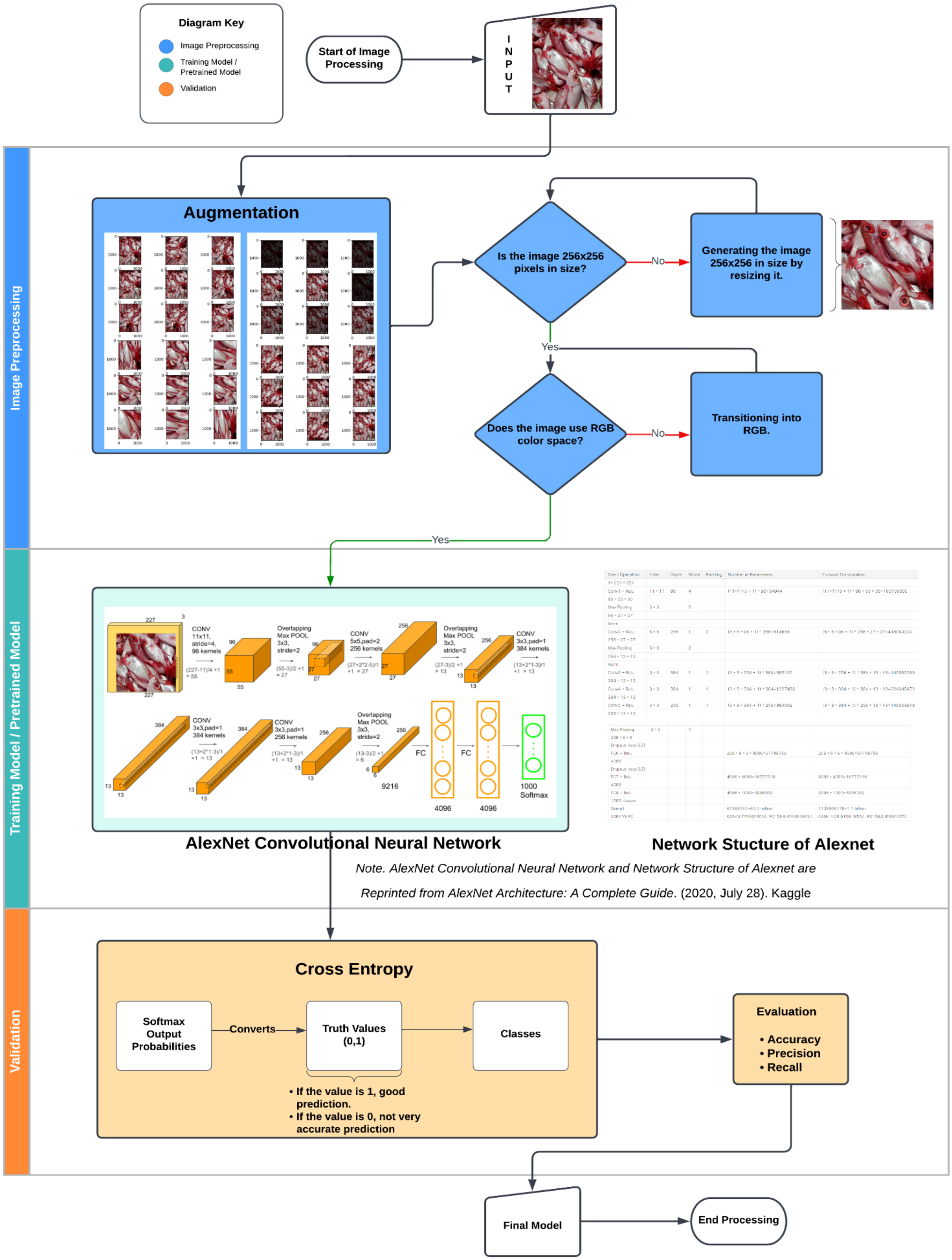


Figure 11: **Image Processing Flow Chart**

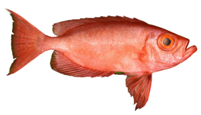
	LOCAL NAME	ENGLISH NAME	SCIENTIFIC NAME
	Buraw	Island Mackerel	Rastrelliger faughni
	Kwaw	Red BigEye	Priacanthus macracanthus
	Sapsap	Splendid Ponyfish	Leiognathus splendens
	Turay	Fringescale Sardinella	Sardinella fimbriata
	Turingan	Bullet Tuna	Auxis rochei

Table 8: **Class Labels**

3.4 Testing and Validation

The probabilities from CNN's softmax will be turned into true values using the Cross-Entropy approach once the CNN has processed the image. For the trained model to produce results that are as near to the intended result as possible. The model is then evaluated for accuracy, recall, precision, and Categorical cross entropy.

The codes and processes involved are being evaluated. Four evaluation metrics will be used to assess the trained model.

The first evaluation metric is accuracy with the formula:

$$\textbf{\textit{Accuracy}} = \frac{TP + TN}{TP + TN + FP + FN}$$

Wherein:

True Positive (TP)

True Negative (TN)

False Positive (FP)

False Negative (FN)

The second evaluation metric is precision. Precision refers to how accurate/precise your model is in terms of how many of the positive outcomes that were predicted turned out to be positive. The formula is:

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

The third evaluation metric is recall. Recall determines how many Actual Positives our model actually captures by classifying it as Positive (True Positive). The formula is:

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

The fourth evaluation metric is Categorical cross entropy. In multi-class classification problems, categorical cross entropy is a loss function that is used.

$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij} log(p_{ij})$$

Wherein:

N - Number of Rows in the Test set

M - Number of Fault Delivery Classes

Y_{ij} - 1 if observation belongs to Class j; else 0

P_{ij} - Predicted Probability that observation belongs to Class j

The mobile application will also be evaluated. The accuracy of the mobile application will be compared to 100 randomly selected individuals. The average time it took the mobile app and the humans to identify a fish species will also be compared.

3.5 Coding

This phase involves pre-processing the images, building a model based on the AlexNet CNN, and developing a mobile app that employs the model. The anticipated designs in phase two were taken into account when developing mobile applications in this phase.

As this study will require a large number of images for training, the researchers intended to take data augmentation into account. This will create new samples from existing images that will enlarge the training dataset and improve the prediction accuracy. This also deals with the class imbalance since the researchers intend to enlarge the number of image samples belonging to classes with insufficient count. Once the dataset is obtained, the images will be pre-processed by cropping, resizing, rotating, and sorting. Duplicate images will be also removed then the dataset will be divided into training, validation, and testing datasets in the following ratios: 80:10:10, 60:20:20, and 70:20:10. Each dataset variation's prediction accuracy will be determined by the metrics given throughout the testing phase.

CNN model will be created trained with the dataset allocated for training. The validation metrics described in phase 4 will also be implemented in this phase on various ratios then the dataset version with the best result will be selected to be exported into a model in .tflite file extension.

Upon android app development and model embedding, the tflite model will be imported into the app as a core in fish detection. In order to do that, tflite flutter plugin will be added as a dependency in pubspec.yaml file which is a file that contains plugins and resources links needed by an app. This plugin allows the model in tflite file format to be loaded in flutter apps.

OpenCV library will be employed in order to have access to static and real-time frames from the camera as input for the model to recognize fish species.

3.6 Application Development

The design and functionality of the prototype will be integrated into a solidly constructed software application using Flutter to further improve it. Flutter is a lightweight UI toolkit for building apps that integrates with pre-existing code. Dart is the programming language to utilize. It aspires to offer the most productive programming language for cross-platform development with a flexible execution runtime platform for app frameworks.

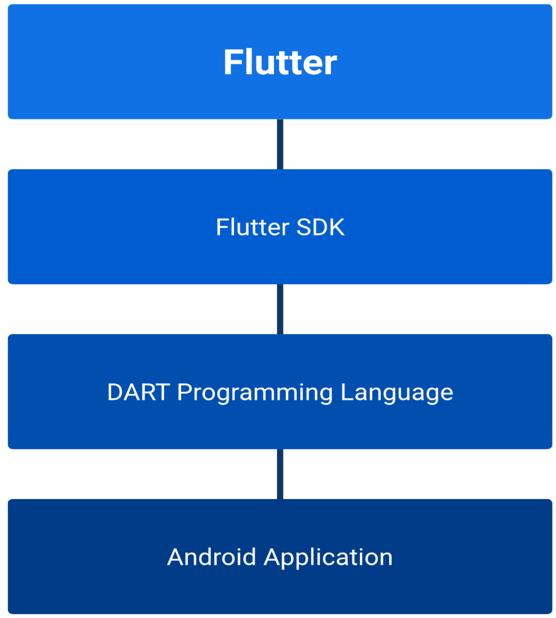


Figure 12: **Application Development Flow Chart**

3.7 Model Embedding

For the developed application to function to its intended use, the embedding of the model towards the build application will occur. After saving the final model to a TF Lite file format, it will be imported into flutter using the TF Lite plugin.

Phase 4: Cutover

The well-developed software application will then be deployed during this phase. It comprises user training in addition to data conversion, testing, and phased rollout to the new system.

The accuracy of the developed mobile application will then be evaluated by comparing its performance to that of humans. Verifying that the model works accurately and provides the desired information for identifying the species of fish. The output of this study is a mobile application that identifies five specific fish species under FMA 7.

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