AUTOMATIC IDENTIFICATION OF ETHIOPIAN CULTURAL CLOTHING USING DEEP LEARNING

A Thesis Presented

by

TAMIRAT AKLIL ZEMEDE

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In Partial Fulfilment of the Requirements

for the Degree of Master of Science

in

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ACCEPTANCE

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June 2024

DECLARATION

I, the undersigned, declare that this thesis work is my original work, has not been presented for a degree in this or any other universities, and all sources of materials used for the thesis work have been duly acknowledged.

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This thesis has been submitted for examination with my approval as advisor.

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June 2024

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LIST OF ABBREVIATIONS

Bi-LSTM	Bidirectional long-short time memory
BN	Batch Norm
BN	Batch normalization
CNN	Conventional neural network
CONV	Convolution
DNN	Deep neural network
DO	Dropout
FN	False negative
FP	False positive
GRU	Gated recurrent unit
HOG	Histogram of Oriented Gradients
LSTM	Long short-term memory
MCNN	Multiple Convolutional Neural Network
MCNN	Multiple Convolutional Neural Network
MLPs	Multilayer Perceptions
POOL	Pooling
RAM	Random Access Memory
RNN	Recurrent neural networks
TN	True negative
TP	True Positive
VGG	Visual Geometry Group

ABSTRACT

Ethiopia is known in different Cultural clothing in Fabrics, design and colour based on Ethnics, Geographical Location and their religions. Peoples of Ethiopia different cultural clothing is their conventional clothing on occasion of different ceremonial events. To identify such different cultural cloth it needs human expert this method consumes time and man labour and for clothes nearly the same fabrics it is difficult to identify with human eye vision. Previously there was no developed model to identify Ethiopian cultural cloth to overcome this problem we use deep learning CNN Model to classify selected cultural clothing of Ethiopia. : Different Ethiopian Cultural clothing image collected from Different area, such as from Oromo cultural centre, Ethiopian Minister of Culture and tourism, Ethiopian Regional states media and their cultural centres. We classified image into sixteen way Softmax classifier was used for categorizing into specific classes (i.e., of Afar, Amhara, Beshangul Gumuz, Dawro, Gambella, Gurage, Hadiya, Harari, Kaffa, Kambata, Oromo, Sidama, Siltie, Somali, Tigray and Welayta). We collected 11,200 each class 700 images and from total image 80% of image used for training and other 20% for validating the Model. Those collected image resized into equal image size of 224x224 image pixels. After compared CNN with Three, five and Seven Convulation we get Model CNN Contains Five Convolution Layer Feature extraction each layer with kernel size 3x3, Maxpooling 2x2 and Bach normalization, Last Layer with Flatten Layer and to identify the result we used Softmax activation. Final we get image accuracy of 97.21. This model Recognizes and classify commonly dressed Ethiopian cultural cloth also This model in Ethiopia commonly dressed but, they are not Ethiopian cultural cloth classified as unknown. This research overcomes the needs of experts and everyone who wants to buy and identify capture image and identify automatically.

Keywords: Cultural cloth, Deep learning, CNN, Neural Network, Clothing Classification, Convolution Layer

CHAPTER ONE

INTRODUCTION

1.1 Background

Ethiopia which has above 80 Ethnics group with different cultural clothing, having own language, culture, clothing and living tradition officially recognized by the Ethiopian government in 2007 Ethiopian National Census [2][25] Ethiopian cultural clothing is one of income to the country through selling to the tourist and Local peoples. It produced through hand weaving and different textile industries. [2]

Ethiopia's weaving tradition is centuries old custom. Historically, farmer would grow a small plot of cotton. The family would harvest the cotton and the women would clean it, card it and slowly hand spin it into thread. The farmers would wait for the travelling weaver to come to their part of the country. He would weave all the clothing and blankets the family would use for the year. [1] Today, weaving is still a pillar of Ethiopian culture. Most Ethiopians wear hand woven, white clothing at all ceremonies and holidays.[1] Weavers traditionally weave four different types of fabric; those are Kemis, Netela, Gabi and Boluko.[2] Kemis, cloth used to make women's dresses; Netela, could be an exceptionally lean and fragile delicate scarf made from cotton; Gabi, a thicker weave made into a blankets worn to protect from cold or on the beds. The final Boluko is thicker than Gabo while Gabi is thicker from Netela, all made from Traditional waiving of cotton. These textiles differ in their texture but they are traditionally all white, using white cotton. The colourful edging found on most traditional clothing this colourful edging is pillar to identify to which cultural cloth belongs to It made using imported polyester or rayon threads. Generally weaving is a craft handed down from father to son and is traditionally done by men.

Skill used for waiving classified into three different artisans those are: a woman to spin the cotton into thread, a man to measure the threads for the warp and tie them onto the loom then a woman to prepare bobbins of thread to be woven and another man who will weave the textiles. Weaver uses horizontal two-harness treadle looms with a maximum width of 80cm to hand weave cotton. They also use large looms with flying shuttles. Ethiopian cultural clothing is widely dressed on ceremonial occasion such as: Celebration of New Year, Epiphany (timket), Christmas (Gena), and Irrecha (Thank giving) and for different Religious ceremony.

In August 2022 Ethiopia divided into 12 Regional state and 2 city administration those are Afar , Amhara , Benishangul-Gumuz , Central Ethiopia , Gambella , Harari , Oromia , Sidama ,Somali , South Ethiopia , South West Ethiopia , Tigray , Two City Administrations: Addis Ababa and Dire Dawa [19]. Ethiopian cultural clothing different based on geographical location Ethnic group and Based on Religion. Identifying Ethiopian Cultural clothing Difficult since Ethiopia is rich in Different cultural clothing. From machine learning deep learning is highly used for extracting feature [41] Conventional neural network (CNN) is a part of deep learning mostly used for image recognition and feature extraction.

The Ethiopian cultural clothing is not only from cotton as an example the ladies of Oromo and Sidama people groups favour calfskin articles and Affairs are inclined to wear brightly colour wraps made of cotton whereas Harare decorate themselves in purple, ruddy, and dark dresses. Habesha cloth is popular in Tigray and Amhara they used in different style and colour that makes different from one another. In expansion to the dressing fashion there are other properties which separate these locals in our nation. Such as hair styles, gems, weaving designs that make a difference to recognize each tribe and ethnic bunches in our nation.

To solve such diverse cultural clothing we have proposed image processing and deep neural network as our model to classify to each class. Based on 12 regional state we selected 16 types of cultural clothing style, Ethiopian Regional Majority inhabitants are considered. Those are Afar, Amhara , Benishangul-Gumuz, Gambella , Harari , Oromia, Sidama Tigray, and from newly established regional state not ethnic based South , south west and Central Ethiopia We considered 7 type of Cultural cloth based image data and resource availability. The seven from newly emerged regional states are Gurage, Hadiya, kambata, siltie, Dawro, Welayta and Gamo and Kaffa. Gamo and Welayta share similar [6] clothing style since we choose one from both of them Welayta Cultural cloth.

1.2 Motivations

Ethiopian cultural cloth now days popular in ceremonial events and the demand of such cloth is increasing from previous. The identification of such cloth belongs is using manual using human vision. This method of identification is time and human labour consuming and it accuracy depends on experience and human labour. Identifying using machine learning it doesn’t need any expert and its accuracy for those much similar cloth style better than human vision.

1.3 Statement of the Problem

Country such Ethiopia with above 80 Nation Nationalities with Different cultural, tradition [23] Wear their cultural clothing on different ceremony event such as: Ethiopian New Year, Irrecha [Thanks giving], Meskel, Gena [Christmas] and different Religious and Cultural ceremony. Cloth can represent culture of one country identifying such different Cultural clothing style is difficult since there are some clothes which is difficult to identify by human vision. On commercial Centre cultural clothing is labelled manual such labelling of cultural cloth it takes time and man power. Moreover, this manual distinguishing proof strategy is time and human labour devouring and undesirable, since the effectiveness depends primarily on the involvement and information of experts. From different country Tourist visits Ethiopia from what they visit is Culture of Ethiopia different clothing style is one of Ethiopian culture to distinguish one from another they need expert there is not Model or other on this area previously done. On other hand to buy such varieties cultural clothing visiting many stores makes time consuming. The research issues which have to be addressed in this study have been summarized as:

- How to design and develop Ethiopian cultural cloth identification Model?
- How to classify Ethiopian cultural cloth identification, and which classification techniques is suitable?

1.4 Objective of the Study

1.4.1 General Objective

The General Objective of our research is to Identifying Ethiopian Cultural clothing using deep learning

1.4.2 Specific Objectives

The Specific objective of our model is as bellow:

- To review art of Literature on Ethiopian cultural cloth
- To prepare data set and pre-process Ethiopian cultural cloth
- To build deep learning model and evaluate performance of Ethiopian Cultural clothing

1.5 Method

We used as following methods to achieve our objectives.

Literature Review: Different related Literatures done on deep learning and machine learning Reviewed and their gap identified preferable model identified.

Data Preparation: Different Ethiopian Cultural clothing image collected from Different area, such as from Oromo cultural centre, Ethiopian Minister of Culture and tourism, Ethiopian Regional states media and their cultural centres. Those images collected labelled to specific class based on image taken from Ethiopian Minister of Culture and for those difficult to identify asking experts working cultural centre then labelled to respective group. Deep learning we need to found large amount of data and we found no data collected in one.

Implementation: Our Model implemented on Google colab which freely available which different version such GPU, TRU since this solve high RAM Requirements to train the model.

Experimentation: Our Model result checked how it predict to the right categories and result True label and predicted label compared

1.6 Scope and Limitation

Only Ethiopian Cultural clothing with specified below is considered based on Ethiopian regional state on those are majority inhabitants in areas their cultural clothing and populous clothing style is considered. As August 2022 [19] there are 12 Region and 2 City administrations. From Newly emerged region South, South west and Central Region we considered 9 cultural clothing. From south region we considered Welayta cultural clothing; central region we considered Gurage, siltie, kambata and Hadiya cultural clothing is considered from south west Dawro and Kaffa cultural clothing is considered. Generally 16 types of Ethiopian cultural clothing style are considered those Regional states are Tigray, Amhara, Oromia ,Afar, Benishangul-Gumuz, Harari , Gambella Peoples, Somali ,Sidama, Welayta, Gurage, Siltie, Kambata Hadiya, Dawuro, Kaffa, Cultural clothing. We selected those 16 based on [25] [2] Majority inhabitants in area and Easier to get data Resource other nothing else.

1.7 Significance of the Study

Ethiopia is one of country with different ceremonial event and most common to see different cultural clothing. This research makes for Ethiopian to know their diverse of cultural clothing to identify easily through taking camera and for tourist they don't need of experts while visiting wrought country cultural costume of Ethiopian cultural cloth. This research also supports for different researcher who wants to study on Ethiopian cultural cloth as reference and it can be collaborated with Google image uploaded to categorize to specific groups of Ethiopian cultural cloth.

1.8 Organization of the Thesis

We present in chapter two about 16 different Ethiopian cloth, Deep Learning, Convolutional Neural Network and different Literature reviews presented.in chapter three our CNN Model proposed will presented in details data source discussed. In chapter four Experimental data analysis result of model accuracy of training model specified. Finally in chapter five conclusions and recommendation to our research presented

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In Chapter two considered different Ethiopian cultural cloth in section 2.2 we discuss different Ethiopian cultural cloth, section 2.3 digital image processing discussed in section 2.4 deep learning presented, in section 2.5 Discussed way of preventing Overfitting ,section 2.6 discusses Performance evaluation Techniques, Finally in section 2.7 2.7 different related work of literature presented.

2.2 Ethiopian cultural cloth

In Ethiopia there are more than 122 million populations which make the second populous in Africa and also Ethiopia has above 80 ethnic groups having their own culture. B. Cahoon[19] In August 2022 Ethiopia divided into 12 Regional state and 2 city administration those are Afar , Amhara , Benishangul-Gumuz , Central Ethiopia , Gambella , Harari , Oromia , Sidama ,Somali , South Ethiopia , South West Ethiopia and Tigray , City Administrations: Addis Ababa and Dire Dawa .

Those regional states of Ethiopia have unique culture and tradition most them classified based on majority ethnic group in the area. The central Ethiopia, South Ethiopia, and south west Ethiopia multi ethnic group categorised as regional states. South Ethiopia Regional state [21] consists of 11 zones Ale, Amaro, Ari, Basketo, Burji, Gamo, Gardula, Gedeo, Gofa, Konso , South omo and Welayta zones. Welayta sodo is regional administrative centre. Central Ethiopia Regional state [21] consists of s Gurage, Silte, Kambata Tambaro, Halaba, Hadia zones and Yem special district. South west Region [20] consists of Bench Sheko, Dawro Zone, Keffa Zone, Sheka Zone, West Omo Zone, Konta Zone.

Based on 12 regional state we selected 16 types of cultural clothing style, Ethiopian Regional Majority inhabitants are considered. Those are Afar, Amhara , Benishangul-Gumuz, Gambella , Harari , Oromia, Sidama ,Somali, Tigray, from newly established regional state not ethnic based South , south west and Central Ethiopia We considered 7 type of Cultural cloth based on data source availability

2.2.1 Afar

Afar is One of Ethiopian Regional state Majority inhabitants are Afar People. Afar people are known in nomadic herding. The Land of Afar people live area in known Afar triangle which is world hottest and driest area. Afar people known by their men holding Jile the name Jile also known as Gile in Afar Language which strapped to their waists [8] as Figure 2.1 bellows. Afar people have two unique hair styles those are dayta and asdago. The asdago is afro hair style butter applied on it which makes ashy which protect them from sun. The Dayta is created using stick and butter apply on it which makes elaborate shay. Afar men wear light cotton known as toga with jile strapped on waists and they also wear ornate daggers. Afar women they wear bright coloured bead, brass anklets and heavy earrings with braided hair style and intricate frizzed

Figure 2. 1 Afar Men with their cultural cloth and holding Jile

2.2.2 Amhara

Amhara is one of regional state in Ethiopia they majority of inhabitants are Amhara People. [5] Amhara Cultural clothing Based on Location they have little different such as Shewa, Gojam, Gonder and wollo bete-Amhara they have little different wearing style. Amhara dress know based on style for example Shewa Amhara women wear dress like white linen with scurf on the middle while Gondar tick bottom hem on the back. Gojam Amhara their wearing based on colour they wear green coloured cloth. Amhara men wear Jano which is Hand woven red pattern. Most Time we found on Amhara cultural clothing Ethiopian national flag colures those are red, green, and orange.

Figure 2. 2 Amhara Women’s Cultural clothing

2.2.3 Benishangul-Gumuz

Beshangul Gumuz is one of region in Ethiopia it found western of Ethiopia and place of Ethiopian Grand Renaissance Dam. [22] The Region comprises five indigenous ethnic groups: Berta (also known as Benshangul), Gumuz, Shinasha, Mao, and Komo, from them Berta and Gumuz are populous in the area. Benishangul Gumuz People has unique traditional dress and musical instrument. Many men wear traditional muslim dishdasha, a long white gown common in Sudan and Egypt, and white skull cap. Some people wear plastic sandals

Figure 2. 3 Beshangul Gumuz People in their traditional dress and musical instrument

2.2.4 Gambela

Gambela Region is located in south-western Ethiopia [23] with four administrative Zones: Agnewak-Zone, Nuwer-Zone, Mezhenger-Zone, and Etang Special Zone. In the Region, five ethnic groups are considered indigenous. These are the Anywaa (or Anyuak), Komo, Majanger, Nuer, and Opo. Those ethnic have different style of clothing the capital of gambela located in Anyuak zone, and Nuer is largest ethnic group in the area. Those indigenous ethnic groups belong to Gambela people. The constraints of cloth for female green, orange, blue and white in different style like picture below square on upper side.

Figure 2. 4 Gambella people with their cultural cloth

2.2.5 Harari

Harari is one twelve region in Ethiopia [20] found in eastern Ethiopia. Harari has unique culture and tradition. Indigenous ethnic group in Harari regions are Women wear dresses with made up of black material called tay eraz[24]. The upper on face part apex of triangle at lower part of gown the dress may long up to two meters long. This type of colourful cloth Harari people Wear in bridegroom and in pre-wedding engagement. Harari men wears tight trousers elaborately hand embroidered made of silk; rayon and velvet in these skirts are shorter. Names Gey ganafi while Gey Kofia is means head gear.

Figure 2. 5 Harari Women's cultural clothing

2.2.6 Oromia

Oromia is one of largest Regional state in Ethiopia with majority inhabitants are Oromo ethnic group people. The cultural clothing is different area to area as an example Arsi Oromo, Shewa Oromo, Jimma Oromo, Gujii Oromo, Bale Oromo has same different clothing style however all them belongs to Oromo cultural cloth. Most known Oromo cultural clothing is known as Toga for women for men woya. Wandabo which mad from leather and cotton popular for women with holding sinqee which is look like strike.[3][25].Women Oromo wears Beads, Bracelets and necklaces red with yellow strip on the middle Oromo Gadaa flag colour is popular to found d on Oromo cloth with colour constituents of Black, Red and white. Odaa is sycamore tree is symbol of equality, peace and stability in Oromo Culture. This Oda tree symbol mainly found in bracelets, necklets and also drawn on cloth which it significantly identifies the Oromo cultural cloth. In Irrecha (Thanks giving) from different part of Ethiopia most part of Oromia region wear different style of Oromo cultural clothing and on different ceremonial events this cultural cloth wears.

Figure 2. 6 Oromo Women’s cultural cloth

2.2.7 Sidama

Sidama is one of regional state of Ethiopia Majority inhabitants are Sidama Ethnic group, formerly part of the Southern Nations, Nationalities, and Peoples' Region of Ethiopia. [5] Sidama cultural cloth is look Gamo dinguza which has broken white horizontal stripe with colours black, brownish-purple, and yellows with regular intervals.[6] Sidama men cultural cloth short-sleeved shirt and short pairs trousers while long shirts for female. Sidama cultural clothing mostly wearied on holiday especially Sidama New Year fiche chambalala. In Hawasa area different hand waver and textile are making different cultural cloth. Sidama people’s cultural clothing is characterized by fabric made of cotton or other yarns in patterned combinations of red, black, yellow, and broken white.

Figure 2. 7 Sidama Men’s Cultural clothing

2.2.8 Somali

Somali is one of Regional state of Ethiopia majority inhabitants are Somalis people. Somali people most time women dress cultural cloth known as guntiino [9] it looks similar to Indian sari, it different in it is simple white with red cotton which draped on waist and on shoulder. For day to day activities Somali women wear Baati [9] it is with many pattern long cotton dresses. Somali Regional state is hot in climate temperature to overcome this hot temperature men wear skirt with bright shawl which is suitable for hot climate.

Figure 2. 8 Somali Women’s Cultural cloth

2.2.9 Tigray

Tigray is one of regional state of Ethiopia found in northern Ethiopia. [2] In this region Tigrayan, Kunama and Irob peoples live there. Majority inhabitants in the area are Tigre or Tigrayan people. Dressing style in this area most are hand weaving Habesha Kemis[1] there dress has similar style with Amhara clothing style they most identified by the figure that they carries, colour they used on Habesha cloth most they use their regional flag colour or the way they combs her hair. Tigre people wears as pattern there regional state flag colour red and yellow and Axum Monuments drawn on their different cloth is main identifiers of Tigre cloth.

Figure 2. 9 Tigrayan Women’s cultural dressing

2.2.10 Central Ethiopia

Central Ethiopia is one of from twelve regional state of Ethiopia it is not divided to region based on ethnic it is part of former Southern Nations, Nationalities and Peoples' Region [19] Central Ethiopia Regional state [2] consists of Different Ethnics group Gurage, Silte, Kambata Tambaro, Halaba, Hadia zones and Yem special district.

A, Gurage

Gurage is ethnics and zone names inhabiting central Ethiopia. Women in Gurage they wear head tie whis name in Amharic “shash”. Gurage cultural clothing for women dress yellow colures with black strip on the women wear their head-tie. Gurage adult men wear hand weaver calico known as seferer and Skirts (Ejetebab) also taditionaly female wear Azigrat and men wears Tibtab which made from cotton garment.Gurage mens also wear hat which m,ade from Enewa which is locally names as Wehembua.[6]

Figure 2. 10 Gurage women's with Cultural cloth

B, Siltie

Siltie is both Zone names and ethics groups in central regions. The main contents siltie clothing cotton fabrics are colour; broken white, black and red ochre colours. [7] Women and men of siltie people wear hand weaver or with textile with cotton different pattern and men's wear most time siltie cap it is unique by colour from other cap.

Figure 2. 11 Siltie's cultural cloth

C, Kambata

Kambata people also spelt as Kambata or Kambata are a Cushitic ethnic group that inhabit Kambata people is one of Cushitic ethnic group inhabits region central Region of Ethiopia.[6] There cloth names Tambaro the dress consists of three colours. White, Green, Red and Black

[6] Kmabata people cultural cloth known in wearing their cultural hat Qome, Qome is Hat with colourful as figure 2.12 below;

Figure 2. 12 Kambata's Cultural clothing

D, Hadiya

Hadiya is one of zone names in central region and ethnics names.[4] Cultural clothing of Hadiya through from manual waving to industrialized textile in Hadiya city, Hosaina is capital city of Hadiya zones there are different Waver is found. The constraints colour are black red and with different style as figure 2.13 below;

Figure 2. 13 Hadiya's cultural clothing

2.2.11 South Ethiopia

South Ethiopia is one of Ethiopian region [21] consists of 11 zones Ale, Amaro, Ari, Basketo, Burji, Gamo, Gardula, Gedeo, Gofa, Konso , South omo and Welayta zones. Welayta sodo is regional administrative centre. As [25] Welayta peoples are Majority inhabitants in area.

A, Welayta

The Welayta are an ethnic group and its former kingdom, located in southern Ethiopia. [6] there cloth red, yellow and black dinguza pattern, so Welayta people are also known and recognized wearing clothes made from fabrics with this design. Welayta and Gamo share similar cultural cloth style. [6]

Figure 2. 14 Welayta’s cultural clothing

2.2.12 South West Ethiopia

South west Ethiopia is one region in Ethiopia [20] consists of Bench Sheko, Dawro Zone, Keffa Zone, Sheka Zone, West Omo Zone, Konta Zone.

A, Dawro

Dawro people belong to Omotic speaking language family. Dawro represents both the land and the people. [6]. Cultural cloth constraints White, red, black and green. Dawro women’s wears cotton dress in hand waivers or from textile red colour from bottom and wear shash which made from cotton similar with scarf

Figure 2. 15 Dawro’s Cultural cloth

B, Kaffa

Kaffa society consisted of submerged occupational castes engaged in ironwork, wood curving, leather work, pottery, weaving, and gold and silver melting [18] Most of these artisanal craft worker were historically marginalized with a degree of severity that varied by occupation and through time. Kaffa cultural cloth constraints colour in different styles are white blue, pink, dark blue green as figure 2.16 below

Figure 2. 16 Kaffa’s Cultural clothing

2.3 Digital Image processing

Digital image processing is transforming image to digital form for getting useful information. Image used in current world is RGB which is RED, Green and Blue Channels of image pixels. Coloured 16 bit matrices to computers. 65,536 different colours are possible in each image pixels. Three equal sized of matrices is called Channels each having 0 to 255 values. In the RGB images colour black when channels value become (0,0,0)and white when value is (225,225,225. The fundamental in digital image processing are Image acquisition, Image Enhancement, Image Restoration, colour image Pre-processing Wavelets and Multi-resolution Processing, Image compression, Morphological processing, image segmentation, Representation and description, object detection and recognition and knowledge base. Since computer store a finite number of data image processed need to be converted into digital form. Converting image data into discrete digital data is known as digitization. [26] In digital image processing all image data processed in 2D signal. The signal formed from quantized are said discrete signals.

A sinusoid is a periodic function *f* defined by:

$f(t) := A\sin(2\pi(\omega t - \phi)),\ t \in \mathbb{R}$……………………………………………………………[26]

Where A describes the amplitude, ω the frequency, t the time, and the parameter ϕ the phase

2.3.1 Image Acquisition

It is way of retrieving image from the source or external devices. It is transforming Real world image into array of numerical data. Any video capture first sequence of image captured and then converted into manageable entity. Image acquisition possessed three steps those are Optical system which focused from energy, Energy reflected from the object of interest and sensor measures amount of energy. There are different cameras available based of function to take X-ray image Camera (film) used since it is sensitive to x-ray. If we need infra-red image camera sensitive to infrared is required for usual image camera which sensitive visual spectrum is needed.

2.3.2 Image Enhancement

Image enhancement is way of improving the quality of image appearance. The main goals of image enhancements are sharpness, contrast of image, colourfulness blur and noise reducing and correcting distortion and defects. Other techniques for enhancing images are: Morphological transformation, it operates based on Image shape used in binary images and grey scale images. Morphological transformation examples are dilation, Opening, erosion and closing. In python using OpenCV function used such as dilete, erode and morphologyEx. Edge Detection, In python OpenCV performs several function one is edge detection function such as sobel(), canny() and Laplacian() by detecting sharp changes in the image. Colour Correction, In python OpenCV FOR colour correction algorithm used such as cvtColor and inRnage() used to colour balance in the pixels image, white balancing and colour grading. Image Gradients, In OpenCV python function used for image gradients are schar(),sobe() and laplacian() based on highlight changes on image pixels this function can also use for edge detections and image segmentations. Image Cropping, cropping images is way of removing unwanted from area of image using copy make border function create new portion of image. Image Rotation, to change orientation of image from python OpenCV function used are warpAffine function to rotate as required. Image Thresholding, Is used to convert image into black and white by setting threshold value. Function used to set threshold value is threshold function. Image Blending, this is techniques to put two or more images together. From Open CV functions to combine together are add weighted functions. Image deblurring, this deblurring is way of removing blurred image caused by hand shake of camera, edging out of focus or other. Functions used to remove such are wiener functions.

2.3.3 Image Restoration

Image restoration is way of returning damaged image into original one. Different images become distorted because of edging, noise and different factors. Deep learning are highly used based on for defected image replaced by weighted sum Image restoration classified into two those are deterministic and probabilistic. Deterministic is when degradation model is known and fixed using mathematical or physical principles degradation resolved. While probabilistic is when degradation model is unknown using deep learning or machine learning using OpenCV algorithms such as inverse filtering, wiener filtering.

2.4 Deep Learning

Deep Learning is core part in artificial intelligence and flexible to able to learn. Deep learning deals with enhancing and analysing the image. On image enhancing clustering, classification is considered.to achieve image enhancement edge, shape, region, texture and enhancement performed.[24] deep learning is preferable for image analysing and enhancement since model itself perform model analysing and enhancing. Deep learning modelling techniques enable computational models to learn feature representation in data using multiple processing layers and several levels of abstraction [26]. A deep learning model is made up of multiple layers that stack up on top of each other. The first layer is input layer consists of units containing values fed to every neuron, and then the predicted results come out of the model from the output (final) layer. The hidden layers placed between input and output layers apply weights to the inputs and pass them through an activation function. The activation function is used to help the network add non-linearity and learn complex relationships in the data.

A deep learning use multiple processing layers which performs computational analysis in this layer the first layer performs value feed to all neurons then again give to the next layers of neurons. The final layers predicts to predefined classes of model. Activation function performs to add non linearity to the model performing complex relationship.

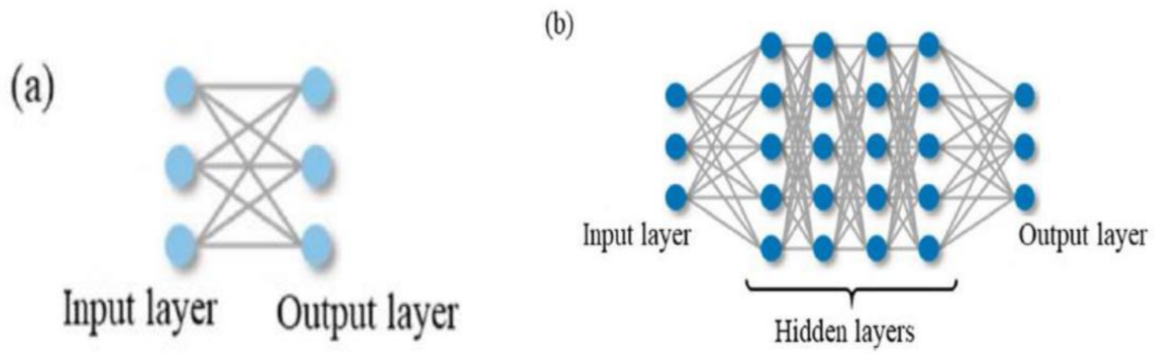

Figure 2. 17 a: Conventional neural network, b: Deep learning neural network [26]

2.4.1 Convolutional neural networks (CNN)

CNN is part of machine learning known image analysing with deep learning approach by dividing into layers. Those layers are Horizontal, vertical input and output layers. A hidden layer is just product of horizontal and vertical layers. [24].

A convolutional neural network is a mathematical construct consisting of several layer types, from several layers we consider: Convolution (CONV), Activation (ACT or RELU), and Pooling (POOL), Fully Connected (FC), Batch normalization (BN), Dropout (DO). All listed layers performed in training phase in CNN model. On other hand activation and dropout are they have also been used to make the architecture of the network explicitly clear.

2.4.2 CNN-LSTM

Long short-term memory (LSTM) can learn long-term relationships in data. [33] However, spatial data like images are challenging to model with the standard LSTM. The convolutional neural network combined with long short-term memory (CNN-LSTM) is based on an LSTM network that is primarily designed for sequence prediction tasks where the input is spatial data, such as images, videos, or temporal structure of words in a sentence, paragraph, or document. The main architecture of the CNN-LSTM model consists of the input layer, convolution layer, pooling layer, sequential layer hidden layers and fully connected layer. The first three layers are the CNN layers. The CNN layers output data is transferred to the LSTM layer. Following temporal modelling, the data from the LSTM layers are sent to a fully connected layer. [34] These layers are well-suited to produce higher-order features that are easy to distinguish within distinct categories. The CNN model is used for feature extraction, while the LSTM model is employed for data interpretation over time.

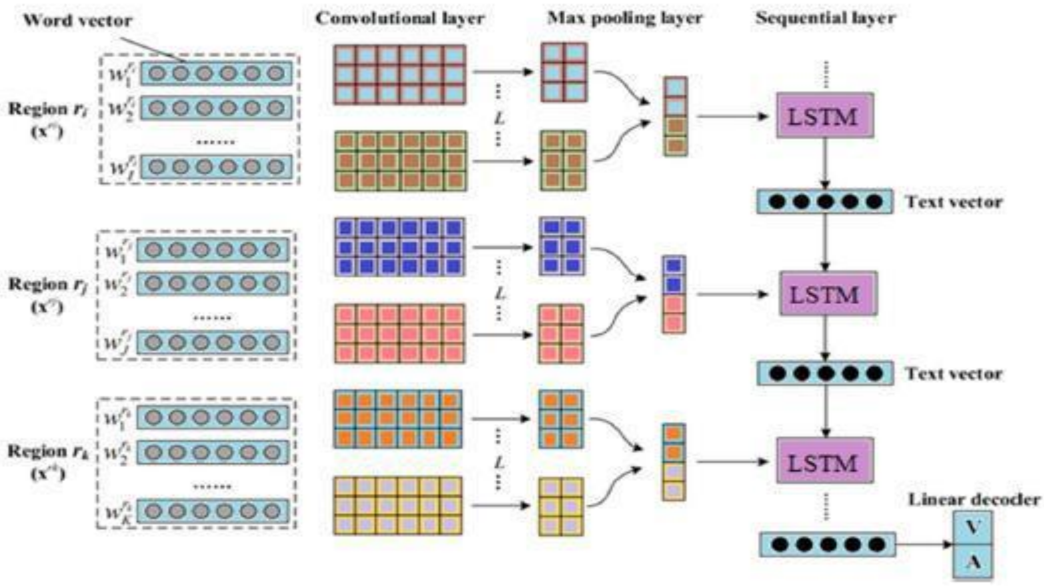

Figure 2. 18 Regional CNN-LSTM model for sentiment analysis [34]

Convolution Layer: It is a central building of CNN with main objective drive input from different characters. Its parameters consist of a set of filters for learning K (kernels) [28]. The width and height of each filter are often almost square in terms of their spatial dimensions, these filters are thin, but extend across the volume's full depth. When dealing with RGB pictures, the depth is the number of channels for CNN inputs. As volumes are deeper in the network, the depth is the number of filters added to the previous layer. K kernels are applied to the input image, and then each kernel is converted to the input volume into 2D.K kernel size can be 3x3 or 5x5 number of kernel choose with no rule just arbitrary. Parameter's that control outputs are Depth, stride, and zero padding. Out volume is depth number of filters in convolution layers by connecting input layers to local regions. [30]

Stride: it is how pixels have to pass the filter over the input image horizontally and vertically. To respective field smaller strides lead to big volumes of output similar with larger stride to smaller values of output.

Smaller strides lead to receptive fields overlapping and larger volumes of output, while larger strides lead to smaller volumes of output. When we use large and small stride see bellow table 2.1 If the input size is NxN and the filter size is FxF, output matrix's become (N-F+1) x (N-F+1) or if input size is Nc x Nr, filter size is Fc x Fn, and the output is Mc x Mx, and the stride number is S, then you can measure Mc and Mx as:

$Mc = (Nc - Fc/S) + 1$

$Mx = (Nr - Fn/S) + 1$

Table 2. 1 Input Image 5x5 with kernel 3x3 filter

5x5 input image

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

Kernel filter 3x3

0	1	2
2	2	0
0	1	2

Table 2. 2 Output of convolution with stride size of 1 (left) and 2 (right)

12	12	17
10	17	19

12	17
9	14

9	6	14

Zero-padding determines the way the input image size is maintained by inserting additional zeros along the image boundary. The output of the 3 x 3 filter applied to the zero-padded 5 x 5 image is shown in Table 2.1 on the left, while the output of the 3 x 3 filter applied to the zero-padded 5 x 5 image is shown on the right. As it is clearly shown, zero-padding helps to maintain the original 5 x 5 image's spatial dimensions.

Table 2. 3 Applying zero-padding (of size 1) to the image on Table 2.1 left

0	0	0	0	0	0	0
0	3	3	2	1	0	0
0	0	0	1	3	1	0
0	3	1	2	2	3	0
0	2	0	0	2	2	0
0	2	0	0	0	1	0
0	0	0	0	0	0	0

Table 2. 4 Effect of zero-padding on output image size

6	14	17	11	3		6	17	3
14	12	12	17	11		8	17	13
8	10	17	18	13		6	4	4
11	9	6	14	12				
6	4	4	6	4				

Pooling layer: It is one of block on CNN used to reduce the parameter and computational time gradually pooling layer added on each feature map separately in a way to save the most important details from the feature maps. The most popular approach applied on the pooling layer is Max pooling. Consider a 4x4 matrix shown below on Table

Table 2. 5 Pooling layer operation

Pooling layer stride = 2				2x2 maxpooling output	
1	3	2	1	9	2
2	9	1	1	6	3
1	3	2	3		
1	6	1	2		

Activation function: An Activation function is adding non linearity to layers of networks this leads network model becomes more complex. From many activation functions ReLu is used in hidden layers. For output layers number of output is considered ReLu is used for output layers two for above two outputs Softmax activation is preferable.in when input is negative value is 0 and when input is positive value is 1. [27]

Fully connected layer: A fully connected layer is applied at the end of the network before applying the classifier (most of the time Softmax classifier).It multiplies by input weight matrices and bias vectors.

Dropout: Drop out is used to reduce over fitting by removing low performing layers. The default drop out layers for CNN models are 0.5. It performed after each activation function in case to reduce over fittings.

Batch normalization: Batch normalization used in case of reduces RAM and to tuning the model, it normalizes input data to fine just total sum after normalized becomes one. Also has some drawbacks, such as increased computational cost and memory usage, dependency on the batch size and statistics, reduced interpretability and flexibility of the network, and potential issues with transfer learning and fine-tuning.

2.4.3 Recurrent Neural Network (RNN)

Recurrent Neural networks (RNN) are one part of deep learning model it considers temporal inputs for making suitable task in sequential order. RNN most used in speech recognition, video processing and speech recognition.as limitation of RNN is its short term memory, in order to fill this gap other RNN variants emerged such as long short Term Memory (LSTM), Bidirectional LSTM Bidirectional Gated Recurrent Unit (GRU), and Bayesian RNN.

$ht = (Wxt + Uht+b)$……………………………………………………………………..[33]

From above equation of RNN g() represents activation function and u and W represents adjustable weight h, b matrices and x represents an input vector. RNN model is preferable for models processing of sequential data for leveraging ability to capturing dependencies per time. There are new emerged different types of RNN Models such as LSTM, GRU, BiLSTM as Shiri et.al [33] in year 2023 compare Different RNN models above listed with CNN by dataset Manist Fruit-360 he got CNN Model high accuracy, precision, Recall, and F1-score RNN model preferable to use in video, speech and language processing but, for image processing CNN Model is preferable.

2.4.4 Gated recurrent unit (GRU)

A gated Recurrent Unit [34] is one of RNN model to long short-term memory differ in usage of memory when Compared with LSTM, GRU has fewer parameters, simple network structure, and GRU has high training model efficiency, As a result GRU runs faster than LSTM models. GRUs is used to solve network gradient problem to be fixed. GRU has two gates those are input gate and output gate. Compared with the three gate structures of the reset gate, update gate, the reset gate controls hidden neural network influence. The importance of GRU is its speed on training phase, simplicity of the network and to remove gradient problem on the network.

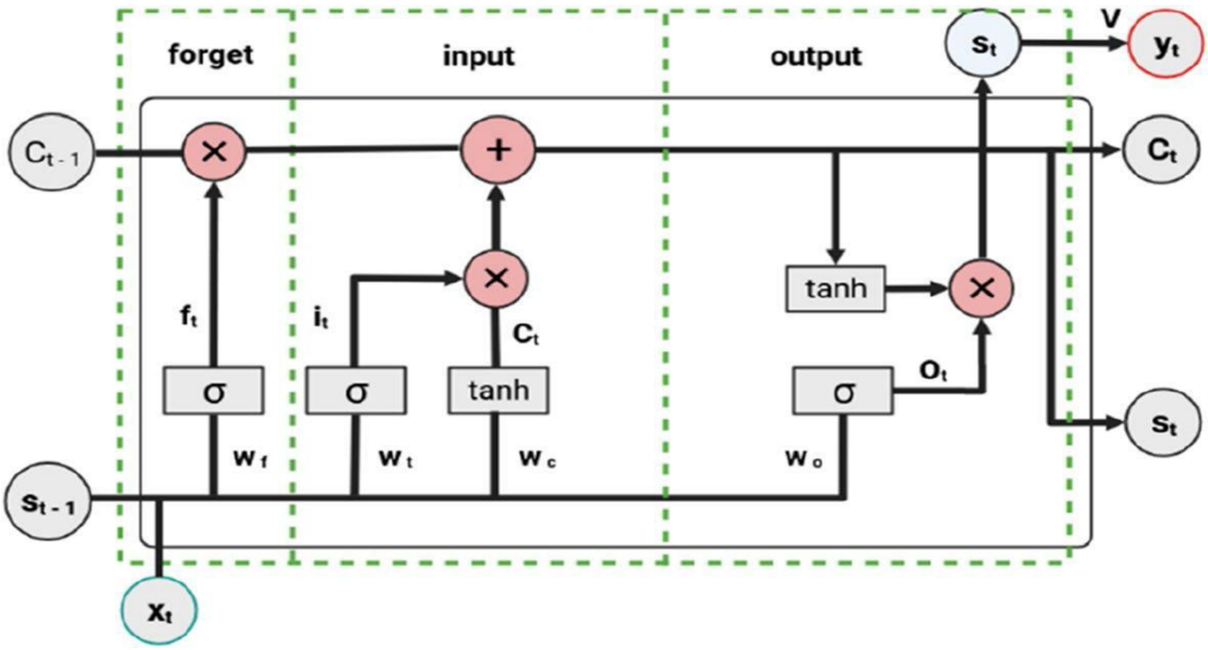

Figure 2. 19 Gated recurrent unit cell [34]

2.4.5 Bidirectional long-short time memory (BiLSTM)

Regular recurrent neural networks with LSTM cells can be extended to bidirectional recurrent neural networks in which the data is passed through two LSTMs [34]. One forward LSTM offers the input sequence in the correct order (forward layer), and another backward LSTM provides the input sequence in reverse order (backward layer). This technique improves the model's accuracy by capturing the long-term dependencies of the input sequence in both directions. In the BiLSTM, the forward layer computation is identical to those in the regular LSTM that computes the sequences.

2.4.6 Multilayer Perceptions (MLPs)

Multilayer Perception is feed forward artificial network (ANN) it is composed of series fully connected layers. New connected Layers become from weighted sum of all outputs. In MLPs input layer is initial layer of the network take input in the form of digital numbers, second it has hidden Layers it processes information taken from input layers. There is no restriction in MLPs number of Hidden layers usually number of hidden layers is small. Back propagation is another characteristic of MLPs and MLP is supervised learning techniques noise or error of the network minimized by fine tuning weighted sum from out put back into the network. MLPs required time to train is short time because of simplicity of the network. They can run on Graphic processing computers (GRU) [34] Application area of MLPs is for data not linearly separable for complex classification and predictive model because of their simplicity. It used in credit scoring, Fraud detection and on customer chum detections.

2.5 Activation Function

Activation function is based on neuron hidden layer and input layer output weighted sum and adding addition biases finally activate result. When weighted sum updated performed. The most populous activation functions are Sigmoid, Relu and Softmax.

A) ReLU

ReLU is activation function used encase of sigmoid function. ReLu used in non-linear and to negative values. Relu reduces problem in sigmoid and tanh expansion and disappearance. ReLu characterized as bellow formulas:

$$ReLu(x) = \begin{cases} x & ,if\ x > 0 \\ 0, & if\ x \le 0 \end{cases} \quad \text{.......} [32]$$

From ReLu equation above when value of x ≤ 0 Relu(x) becomes zero otherwise when input

value greater than 0 ReLu(x) becomes as it's. Relu makes neural network to perform better and have efficiency in terms space and time.

B) Softmax

Softmax is converting output to between zero and one the sum of all becomes one. It predicts to which product it belongs to base on high values registered. Softmax function expressed mathematically as below:

$$f(x) = \frac{\exp(xi)}{\sum_j \exp(xj)} \quad \text{.......} [32]$$

The difference between sigmoid and Softmax is Sigmoid is used for binary classification but Softmax used for multiclass classification.

C) Sigmoid

Sigmoid is non-linear activation function used on feed forward defined for real values on positive derivatives with some degree of smoothness everywhere. Sigmoid function can be represented as bellow:

$$f(x) = \left(\frac{1}{1+exp^{-x}}\right) \quad \text{.......} [32]$$

Sigmoid function used in bilateral classification not used for multiclass classification. Major drawback of sigmoid function is it's during propagation sharp damp gradient, gradient saturation, non-zero cantered and slows convergence.

2.6 Overfitting

Overfitting is when model trained because of noise and unnecessarily data in image class while training increase testing decrease and validation gap high we say the model is over fitting for under fitting vice versa. Over fitting highly occurs in neural networks, to reduce over fitting preferable to be use such as Reduce network size when number of trainable data reduces as well Overfitting also reduced. Early stopping this method is used to ignore noises on early stops. Another one is by adding dropout on training phase to remove small neurons from training the phase the last one is data augmentation when data is small it is easy to remove data seems wrong. In data augmentation image data re checked if wrong image data classified into wrong categories this methods is manually removing wrong data Reduce Network size: Deep Learning is huge it consists Input Layer, Multiple hidden Layers and Output Layer, as hidden layers Node increases the network size also increased to training the model it takes long time and Overfitting also increase while network size increase. Parameters to reduce Overfitting as bellows:

a) Adding Dropout: Adding dropout is the way of removing noise or unnecessary input data from neuron replace by 0.As noise removed the model or network size minimized and Overfitting minimized.
b) Image data augmentation: For reducing Overfitting data augmentation is preferable to use. Image augmentation used by Geometric transformation such as: Crop image, Rotate flip and zoom the image, Colour image transformation this one is by randomly change colour RGB and its brightness contrast by changing it, other is By randomly deleting image and Mixing with other image.
c) Early Stopping: This method is as model train more it model training noises as well. When model Loss get worse it’s better to stop the noise that result in Overfitting minimized.
d) Adding Weight Regulation: A network with Large Weighted result in unstable when small input data changed result in large output changes. To overcome this problem to keep network weight small by adding loss function.
e) Minimizing Network Size: The Network size is in number of layers there are learnable parameters as they increase the network become complex result in

Overfitting to overcome e this its preferable to determine number of layers and learnable parameters on each layer.

2.7 Performance evaluation criteria

Performance evaluation of CNN is Accuracy, precision, Loss and other parameters. Most time data source divided into training, validating and testing data source. Terminologies used in performance evaluations are True positive (TP), True negative (TN), False negative (FN) and False positive (FP), TP is positive data labelled correctly. TN refers to positive data labelled incorrectly. FN refers to Negative data labelled negative while FP negative data but labelled positive. Based on above Accuracy, Precision, Recall, FL score and confusion matrix can be calculated.

a) Accuracy (recognition rate): It is summation of True Positive and True Negative divide bay summation of True positive, True Negative and False Negative mathematically expressed as bellow.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} X100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[30]}$$

b) Precision (Pr): it calculated as True positive divide by True positive plus false positive mathematically expressed as bellow:

$$\text{Pr} = \frac{TP}{(TP+FP)} X100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[30]}$$

c) Recall: it is just measure of completeness when True positive divide by True positive plus True Negative mathematically expressed as bellow:

$$\text{Recall} = \frac{TP}{(TP+TN)} X100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[30]}$$

d) F1 Score: It is Precision times recall divide by precision plus recall mathematically expressed as bellow:

$$F1\ \text{Score} = 2X\,\frac{(PrXRecall)}{(Pr+Recall)}X100 \quad [30]$$

e) Confusion Matrix: Confusion matrix is based on testing data summarizes predicted test data. It is table with size n by n. An entry, CMij in the first n rows and n columns when

Confusion matrix to best all predicted element to in diagonal CM1, 1 to CMn, n number of predicted and labelled similar. In imaginary False Positive (FP) and False True Negative becomes zero.

2.8 Related Work

Nocentini et al, 2022. [17], Image classification for Fashion-MNIST Dataset using four different neural network models to improve image classification Accuracy. The four Neural Networks are Multiple Convolutional Neural Network including 15(MCNN15), MCNN9, MCNN12, MCNN18. They did using CNN model adding LSTM. The model compared with MCC9, MCC12, MCC18, Mobilnet, VGG, VG16, LSTM, CNN, and CNN LeNet-5 from them the new model with Multiple MCNN15 Achieve Accuracy 94.04%. They also tested bay adding more LSTM MCNN18 But they got below MCNN15 too deep neural network faces high gradients. They used Manist dataset online available 60,000 images for training and 10,000 for testing with image size 28x28 grey scale images. Adam optimizer and learning rate 0.01, batch size 64, and epoch 100 they have used. Generally they modified MCNN by adding LSTM in middle layer but, the proposed system if added further fully connected layer since they not used fully connected layer the system performance may further increased and they failed to classify image out of dataset.

M. Elleuch et.al. [2], they proposed clothing classification using Deep CNN architecture based on transfer learning they use model Inception V3 architecture. They use total image 80,000 with 13 classes such as Coat, Blouse, Dress, Vest, Lingerie, T-shirt, Shirt, Poncho, Jacket, Sports sweater, Uniform, Suit, and Sweater all image normalized to 299x299 pixels

From above dataset they use 4100 images for training and validation , for validation 20% of image. With parameter of batch size 32, learning rate with 0.001, RmsProp and optimizer at epoch 20 they get training accuracy of 70% it is better accuracy when they compare with VGG16, GoogLeNet. We see accuracy of their model is still low further need to check and they need to use all images they collected to training model.

Nawaz et al, 2020 [11], they proposed Automatic Categorization of Traditional Clothing Using Convolutional Neural Network based on Google Inception model. They used CNN to automatically identify Bangladesh traditional clothing. They categorized into 5 class managerial cloth and tested with three optimizer SGD, Adam and RmsProp, With Adam optimizer they face over fitting, RmsProp optimize they got low accuracy. They got good accuracy in SGD Optimizer. They used 2 Convulation layer with activation ReLu, with Maxpooling they have five class drops out of 50%. Data set split they splitted into 80/20% mean 80% for training and 20% for validation and testing. Total image collected is 1494 from for training 389 for testing, they Achieved 92.05 training accuracy and 89.22 testing accuracy. .Finally the architecture they used is too small only used with 2 CNN layer time to run is small but more data this architecture is not suitable.

Xu et al, 2022[29] they proposed model comparison between traditional machine learning and deep learning With divide clothing into pure clothing and dressed clothing for pure clothing HOG+SVM algorithm with the Gaussian kernel high accuracy 91.32% as compared with Small VGG network. But for dressed cloth CNN got high accuracy than HOG+SVM small VGG get high accuracy 69.78%. They recommended using for pure cloth traditional machine learning but, for dressed cloth Deep learning. They used Fashion Manist dataset 70,000 images 10,000 for testing and other for training, image size 28x28 grey scales. We conclude that as they tested for research image containing dressed it is preferable to use deep learning.

Hye.et al [14] they proposed A Study on the Clothes Classification using Alex Net Deep Learning they used Alex net classification image clothing and data collected 900 loss images and 1,400 clean images without damage. Total data 2300 image. They nine class from they used model Alexnet shows accuracy about 69.28% on epoch 10 and lr 0.001, while testing accuracy of 76.6%. They confirm when a clean image used more accuracy increased. From above see Research paper shows has poor accuracy need further to test with other CNN Model.

C.-Y. DONG et al. [12] They 78 Used Model Alexnet with Model Accuracy of 93.98.they proposed for pure and clothed clothes checked with R-CNN they found good result in Alexnet but, the model is not stabled. They used fully connected layers with 4 NN compared with MobileNetV1, MobileNetV2 to classify from Fashion Manist total image used 100,000 they image classification with CNN has High accuracy.

X.Zhang et al. [13] Proposed clothing fashion classification for continuous 8 years cloth they use model of deep neural model segmentation and fusing by multi scale convolutional feature extraction they proposed this since they fashion changed year to year to overcome this problem they goes 8 years back after collected image data they get better classify closed fashion by avoiding image back ground. The image collected total of 9,339 with image resolution 384x768 captured from fashion show. They classify image within the same years as one grouped into 8 class based on year. From 9,339 8,000 images used as training while 1,339 as test set, and learning rate set to 0.00001, SGD optimizer batch size 2 in each iteration, and epoch of 64. They get high accuracy of 74.74% with colour RCC-256 colour codes. Using Model Alexnet they get 69.8% they proposed model Deep learning image body segmentation Multiple CNN feature extraction they get accuracy of 80.05% From their model they used large image size which makes network size to become large and result in Overfitting and they accuracy still poor

Raden et al, 2023. [15] They Proposed Clothing type classification using convolutional neural networks by using two type of presumption Convolutional Neural Network and multilayer perceptron architecture. They used image size of 500x400 with this large pixels size they compared both Adam and SGD optimizer final they better accuracy on SGD optimizers with accuracy of 81.05%. We conclude here for large image size as SGD optimizer is preferable but not compatible with small dataset

Marianna et al, 2018 [16] they proposed Clothing identification via deep learning: forensic applications by using popular logo and brand images on this the model correctly classify to respective class. They used deep learning algorithm Alex net Model image from online

Fashion Manist 5549 images for training, batch size 128, epoch 30, learning rate 0.01, class 70, image data 256x256 since this image size is big for surveillance reduced to 32x32. Based on Image quality for high image quality model classify good with accuracy reach 75.3% while the training loss reached 0.07, for low image quality model classify poor. We conclude Alexnet with specified above architecture have got satisfactory result but, Since Alex Net IT with five CNN if further modified based on model may reach high accuracy because of accuracy result is still not good

Jember et.al [31] from Bahirdar University proposed in 2021 end to end CNN on Classification of Ethiopian Habesha kemis fabrics. He classify in five classes based on fabrics design. Machine learning used for feature extraction Gabor Filter with CNN 96% Achieved by using Gabor filter Accuracy increased to 99%.As we see his Model he tried to use more filter before CNN training phase his Data is too low which is for each five classes he used 110 image if we divide into training, test and validation, as he stated from training 80\20 110 of 80% is 88 for training this image too much small for deep learning. He compared different optimizer Adam 0.0001, epoch 32 and image size 256 get high accuracy.

Y. Seo and K. Shin [34] they proposed Hierarchical Convolutional neural Network for fashion image classification its main task is image classification this hierarchical CNN is useful for hierarchical data predicting. Data set they used image of 50,000 for training and 10,000 images for test data. With image size of 28x28 pixels and classify into 10 classes those are trouser, t-shirt, sandals, bag, coat, pullover, ankle boot, dress, sneakers and shirt. They compared the result with VGG16, VGG19 CNN Model They get on VGG16 accuracy of 92.89% and loss 0.4644. Their experiment result in H-CNN Model with VGG16 and VGG19 get high accuracy performance. The model VGG16 and VGG19 used for large data scale since there network size is large for small data set not preferable.

Yuhan.et.al[32] proposed comparison between ReLu activation function with ELU.GELU,PReLu, SerLU LReLu with Manist dataset image size of 28x28 drop out set to 0.2 ,iteration 100 , 3x3 convolutional layer and Maxpooling of 2x2 the model with activation function ReLu perform high Accuracy and precision. But, for speech recognition Leaky ReLu performed high accuracy while PReLu need more feature development.

Table 2. 6 Summarized Related work

no	name	Tittle	Year	Model used	Research Gap	Accuracy
1	Nocentini	Image classification for Fashion-MNIST Dataset	2022	MCNN15	image size is 28x28 that means it exclude some image features	94.04%
2	M. Elleuch et.al.	Ethiopian Traditional music classification	2020	Inception V3	Poor accuracy and they have not use all image they collected	70%
3	Nawaz et al	Based on Google inception automatic categorization of Traditional cloth	2020	2CNN Layer	number of image they used is small they used 1494 image	92.05
4	Xu et al,	Traditional and machine learning comparison	2022	Traditional algorithm HOG+SVM and CNN	they compare different algorithm, there algorithm is not preferable for large data	91.32
5	Hye.et al	Clothes Classification using Alex Net Deep Learning	2020	Alex Net	Low accuracy Further need to tested with other model	76.6
6	Li et al	Dragonfly and Online sequential Extreme Learning Machine for pure clothes	2018	Alex Net	Low stable	93.98
7	X.Zhang et al, al	Human body segmentation and fashion classification	2018	Multiple CNN	It Focus on dressed cloth	80.05
8	Raden et al	Proposed Clothing type classification using convolutional neural networks by using two type of presumption Convolutional Neural Network and multilayer perceptron architecture	2023	RetinaNet with ResNet-152	Further need tested with deep learning algorithm	92.91

9	Marianna et al	They proposed Clothing identification via deep learning: forensic applications by using popular logo and brand images on this the model correctly classify to respective class.	2018	AlexNet	Low Accuracy Result	75.3
10	A. Jember	end to end CNN on Classification of Ethiopian Habesha kemis fabrics	2021	end to end CNN with Gabor filer	Image data used is small only 440 images for training	96

In summary, as many researcher above listed for image classification on modified CNN they get high accuracy and compared with Model with online available model. Need to modify model based on dataset most of researcher they used data is online available data for research data collected not used available to fit. Finally we going to develop our model end to end CNN

CHAPTER THREE

MODEL DESGIGN AND PROPOSED METHOD

3.1 Introduction

In this section brief over view of suggested model and methodology used data resource gathered image prepossessing will presented .In section 3.2 problem identified presented , in section 3.3 data collection and sampling techniques presented in section 3.4 system architecture diagram presented, in section 3.5 CNN architecture of our model presented, in section 3.6 CNN architecture elements used in our model described, in next section data collected, image training, validation and testing phase described at the end summary of this chapter presented.

3.2 Problem Identification

In this section the research problem and relevant solution is stated. Different techniques identifying based on colour, pattern, and design of the cloth will be explored and researched in order to get an awareness of many techniques of classifying different cultural cloth types and patterns. In related research papers, we have examined the holes and presented how we fill in the gaps. Different literatures are checked and the unique Ethiopian cultural cloth which different in design, pattern and colour. Those Different Cultural cloths to identify a person not in that area it is difficult why this research is needed.

3.3 Data Collection and Sampling Technique

The data is collected from different site such as for Oromo cultural centre, From Ministry of tourism and culture of Ethiopia, Regional tourism centre websites and image extracted from video with has cultural clothing. We categorize image data based on cultural image taken from Ethiopian tourism and culture and regional cultural centre websites and by asking experts which work on cultural centre and we have labelled into the predetermined categories. The datasets have classified into training and testing dataset. Image collected different site with size 224x224 and 225x225 image taken from online. For our research we used image by resizing 224x224 into equal image size.

3.4 System Architecture

Data Collected from Different site classified into Training, testing and validation we used image as unknown images not belongs to listed 16 Ethiopian cultural cloth selected.

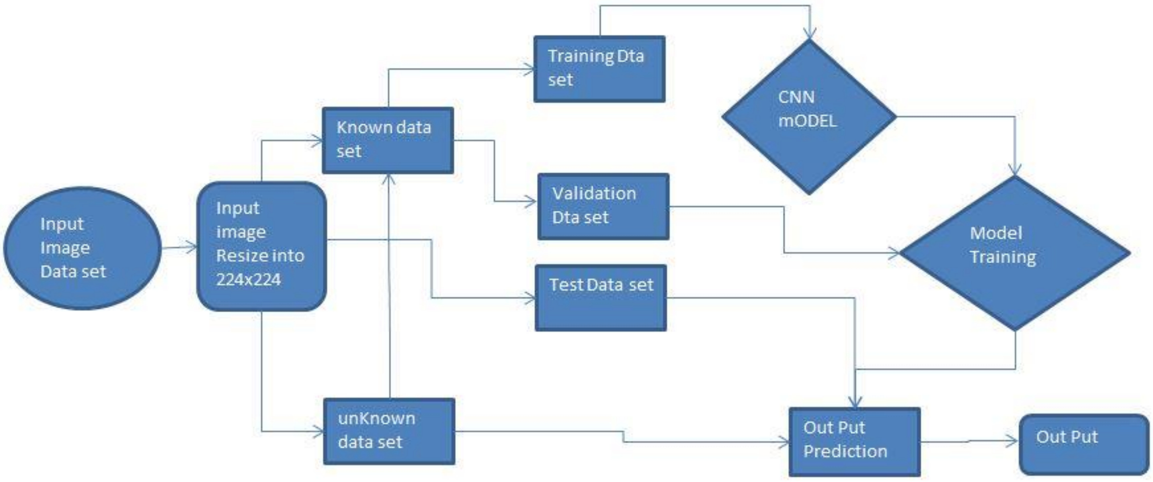

Figure 3. 1 System Model Architecture

From system Figure 3.1 system architecture above input image dataset collected from different areas Resized into 224x224 , Data set contains images with identified and classified to their respective class based on experts and additional images not Ethiopian cultural cloth collected and each image classified as training, testing and Validation. After the Model is trained using model Testing data set and other unknown image predation performed Finally Output result predicted.

3.5 Model Design and Experimentation

Ethiopian cultural cloth identification has designed based on steps in digital image processing such as: The first one is image pre-processing; second feature extraction the third is image classification. In CNN Convulation Layer and Pooling layers uses as feature extraction, in classification Relu for middle layer and Softmax for end layer used. The model implemente on Google Colab is a hosted Jupiter Notebook adding model layer through as necessary. Total layers of our models are 13 layers with five convolution networks.

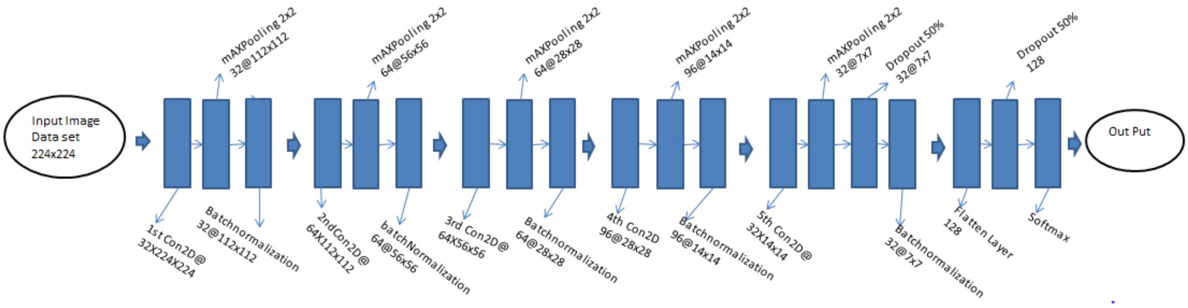

Figure 3. 2 Our designed CNN Model architecture

3.6 CNN Model Architecture

From components Digital image processing image Preprocessing, feature extraction and classification CNN model Convolution and pooling layer perform extraction of image, in classification part activation function such as for middle layer Relu and for end layer Softmax used. The model passes three main parts those are training, testing and validation. We used Keras sequential by adding one layer at a time. Model proposed consists five convolution layer the first layer 32 neuron depth with padding same and kernel filter 3x3, Maxpooling 2x2 and Bath normalization each convolution. The second convolution layer is with 64 convolution depth padding same with kernel size 3x3 similar with Maxpooling 2x2 and bath normalization. The third convolution 64 neuron depth with Maxpooling 2x2 l, after bath normalization performed. Our Fourth convolution Layer has Network depth of 96 padding same and kernel size of 3x3 Maxpooling 2x2 here we used drop out of 50% to prevent over fitting in our mode. Our last convolution layer with network depth of 32 Maxpooling 2x2 network dropouts of 50%., on each convolution layer we used Relu as activation function.

The first is the convolutional (Conv2D) layer. It is like a set of learnable filters. We choose to set 32 filters for the first conv2D layers and 64 filters for second layers, 64 filters for third layers, 96 filters for Fourth layers and 32 for the last ones. Filter transforms a part of the image (defined by the kernel size) using the kernel filter. The kernel filter matrix is applied on the whole image. Filters can be seen as a transformation of the image and batch normalization and Maxpooling2D 2x2 are used over all Layers. The last layer is Flatten layer with network dense 128 activation we used ReLU and 25% of drop out finally we used Softmax activation functions with dense of our length of class in details check below Figure 3.3

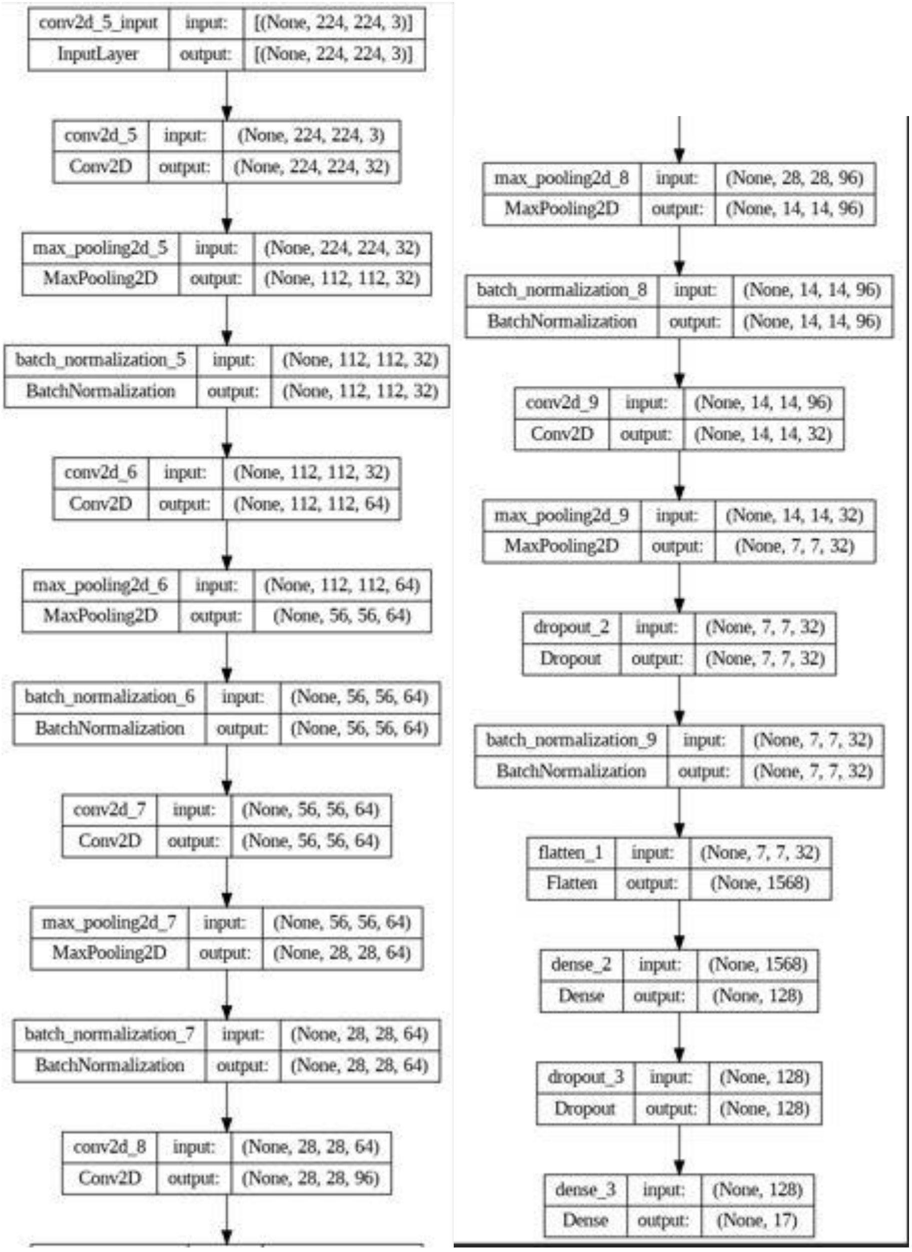

Figure 3. 3 Model processed

3.7 Image Data Preprocessing

Image processed from Online available, Ethiopian cultural cloth shops and image extracted from Cultural music which has cultural cloth dressing, We have used total of 11,200 image for each 16 culture of clothing style 560 image with different image size for training and 140 images for each validation and testing. Image format jpg, jpg and PNG are used. Image collected from different source resized to equal 224x224 image pixels size. All image collected classified to their right class.

Table 3. 1 Sample Images of Ethiopian cultural cloth

No:	Clothing cultural style	Image Collected	Training	Validation	Image collected from
1	Afar	700	560	140	Minister of Culture and tourism, Afar TV, Afar mass media agency
2	Amhara	700	560	140	Minister of Culture and tourism, Amhara Media Corporation(AMECO)
3	Beshangul Gumuz	700	560	140	Minister of Culture and tourism, Benishangul Gumuz Media
4	Dawuro	700	560	140	Minister of Culture and tourism, Dawro Media Network
5	Gambela	700	560	140	Minister of Culture and tourism, Gambella Media
6	Gurage	700	560	140	Minister of Culture and tourism, EMAT GURAGE MEDIA
7	Hadiya	700	560	140	Minister of Culture and tourism, Hadiya Media Network-HMN
8	Harrari	700	560	140	Minister of Culture and tourism, Harari Mass Media Agency
9	Kaffa	700	560	140	Minister of Culture and tourism, dolgado Tube
10	Kambata	700	560	140	Minister of Culture and tourism, Amba Media
11	Oromo	700	560	140	Minister of Culture and tourism, Oromo Cultural Centre
12	Sidama	700	560	140	Minister of Culture and tourism, Sidama Media Network(SMN)
13	Silt’e	700	560	140	Minister of Culture and tourism, Worabe Tube
14	Somali	700	560	140	Minister of Culture and tourism, Jigjiga Tube
15	Tigray	700	560	140	Minister of Culture and tourism, Tigrai Tv
16	Welayta	700	560	140	Minister of Culture and tourism, Wolaita TV

17	Other(unknown)	700	560	140	Taken most common clothed in Ethiopian which not belongs to Ethiopian cultural cloth

3.8 Cultural cloth identification using CNN

CNN used in automatic classification in digital image used highly as model contains 5 convolutional layer we drop out on fourth, fifth and on flatten layers by 50%. Model Network activation, Optimizing and Validation performed in CNN. Softmax and ReLu are most popular activation function when Softmax changes classification output value into numbers between zero and one. ReLu changes negative and positive input into zero and 1 respectively.

3.8.1 Activation Function

For above two classes of image classification Softmax and ReLU are preferable. ReLU used to handle non linearity to prevent negative input damage system performance used in place of SIGMOID activation. Softmax used at output layer all sum output to one. Output layer become between zero and one.

3.8.2 Optimizer

Adam optimizer it has quick convergence output when compare with other different optimizer. It performs by calculating first and second gradient of moments using different parameters. It inherent from both RmsProp and Adagrad Optimizer, for our research Adam optimizer selected as most researchers approve it has high accuracy.

3.9 Model validation

From Keras Preprocessing we split data collected by 0.2 for validating training. Training data uses more data when compared with other testing and validation the reason why is training is required to have more features to train and to predict images outside of data source.

3.10 Testing phase

This process would proceed in the same manner as the training phase. We must pre-process the picture in the same way as we did during the training phase. We often locate the area of interest in the image and use feature extraction techniques similar to those used in the training process. Following any other approach would result in inaccurate classification results since the model will be faced with patterns (inputs) that it is unable to categorize. Similarly, feature learning is carried out in the same way as training by using the learning model generated during training. Unknown samples (i.e., testing dataset) are used for testing the trained model.

3.11 Recognition

The knowledge acquired from the learned model is used to conduct recognition. The training and evaluation datasets are used to learn and validate the designed model. We can classify each image (in the testing dataset) into a particular or predefined class using the information from the trained model. For recognition Softmax activation is used on end layer.

3.12 Evaluation Technique

The model evaluated by confusion matrix of our testing data Based on True predicted and True labelled. Also evaluated with accuracy of model training Based on performance metrics by evaluating output performance assessment observed.

3.13 Summary

The architecture of an Ethiopian cultural Cloth Identification Model based on deep learning image Preprocessing dividing into training, validating and testing discussed in this chapter. We chose model end to end CNN all feature extraction and recognition process ends on CNN Model. Training, testing and validation performed using Keras processing CV. For testing the same protocol used as training.

CHAPTER FOUR

EXPERIMENTAL RESULTS AND DISCUSION

4.1 Introduction

Experimental analysis of Ethiopian cultural cloth Identification described in detail in this chapter: The model performs classification and recognition was approved by different experimental assessments. As we described in chapter three, Total image data source collected are 14,280.We have used 840 images per class of Afar, Amhara, Beshangul Gumuz, Dawro, Gambella, Gurage, Hadiya, Harari, Kaffa, Kambata, Oromo, Sidama, Siltie, Somali, Tigray and Welayta cultural cloth. We used end to end CNN for our model with Convolutional layer adding one another with CNN based feature extraction.

4.2 Dataset

Data collected from different sources such as from online Ethiopian cultural cloth websites, from video with full of cultural cloth of different Ethiopian culture images, by capturing local market found in Addis Ababa. Data collected from each 16 classes are 700 images with total of 11,200. Additional for unknown image i.e. those not belongs to Ethiopian cultural cloth image of 700 collected.

Figure 4. 1 Image collected samples

4.3 Experimental setup

Experiments are conducted on Google collaborator Jupiter Notebook. The collected image data source split into training, Validating and testing. From collected data set for training 80% of data source while testing and validation 20% of data source used. The training contains the largest amount of data because of extracting different features during training is important for the model performance. For testing 20% from training was used total number for training 9,520 for each class while for 2,380 was used ,for testing each image data collected with similar in training phase it is just 2,380 image data used for each class of 140 images total of 2,380 images used. Ethiopian cultural cloth identification performed end to end CNN Model by adding different layer Bach normalization, Convulation and Maxpooling activation function used are Relu for middle layer and Softmax end layer activation. The input image all converted to 224x224 pixels size.

```
train_ds = tf.keras.utils.image_dataset_from_directory(
    dataset_url,
    validation_split=0.2,
    subset= 'training',
    seed = 123,
    image_size=(img_height,img_width),
    batch_size=batch_size
)
```

```
Found 11900 files belonging to 17 classes.
Using 9520 files for training.
```

```
val_ds = tf.keras.utils.image_dataset_from_directory(
  dataset_url,
  validation_split=0.2,
  subset="validation",
  seed=123,
  image_size=(img_height,img_width),
  batch_size=batch_size
)

```

```
Found 11900 files belonging to 17 classes.
Using 2380 files for validation.
```

Figure 4. 2 Dataset Resizing and split into training and testing

We used about 11,200 image data with size of 224x224 since the original image is big for surveillance and requires large amount of Memory processors.

4.4 Experiment of end to end CNN with Five Convulation

As above, Figure 4.2 image data containing five CON2D layers with three drop out two 0.5 and last flatten layers by 0.25 parameters used in our model Batch size 32, epoch 64, learning rate of 0.001 with image size of 224x224, for each five CON2D Layers Relu activation function and kernel size of 3x3used. The last flatten layer coverts from 2D into 1D layer it becomes easy to recognize using Softmax by classifying number of class with numbers between zero and one.

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_10 (Conv2D)          (None, 224, 224, 32)      896

 max_pooling2d_10 (MaxPooli  (None, 112, 112, 32)      0
 ng2D)

 batch_normalization_10 (Ba  (None, 112, 112, 32)      128
 tchNormalization)

 conv2d_11 (Conv2D)          (None, 112, 112, 64)      18496

 max_pooling2d_11 (MaxPooli  (None, 56, 56, 64)        0
 ng2D)

 batch_normalization_11 (Ba  (None, 56, 56, 64)        256
 tchNormalization)

 conv2d_12 (Conv2D)          (None, 56, 56, 64)        36928

 max_pooling2d_12 (MaxPooli  (None, 28, 28, 64)        0
 ng2D)

 batch_normalization_12 (Ba  (None, 28, 28, 64)        256
 tchNormalization)

 conv2d_13 (Conv2D)          (None, 28, 28, 96)        55392

 max_pooling2d_13 (MaxPooli  (None, 14, 14, 96)        0
 ng2D)

 batch_normalization_13 (Ba  (None, 14, 14, 96)        384
 tchNormalization)

 conv2d_14 (Conv2D)          (None, 14, 14, 32)        27680

 max_pooling2d_14 (MaxPooli  (None, 7, 7, 32)          0
 ng2D)

 dropout_4 (Dropout)         (None, 7, 7, 32)          0

 batch_normalization_14 (Ba  (None, 7, 7, 32)          128
 tchNormalization)

 flatten_2 (Flatten)         (None, 1568)              0

 dense_4 (Dense)             (None, 128)               200832

 dropout_5 (Dropout)         (None, 128)               0

 dense_5 (Dense)             (None, 17)                2193

=================================================================
Total params: 343569 (1.31 MB)
Trainable params: 342993 (1.31 MB)
Non-trainable params: 576 (2.25 KB)
```

Figure 4. 3 CNN model Summary with its parameters

Table 4. 1 Summery of CNN with Five Convulation architecture

Layers	Layers parameter	Activation
Conv2D	32, size(3,3)	ReLU
Max pooling	Size(2,2)	

Batchnormalization		
Conv2D	64, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	64, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	96, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	32, size(3,3)	ReLU
Max pooling	Size(2,2)	
Dropout R	0.5	ReLU
Batchnormalization		
Flatten	128	
Dropout	0.25	ReLU
Dense	128	
Dense	17	Softmax

From above Table 4.1 we see five Convulation layer in each Convulation there is maxpooling with size of 2x2 and batch normalization, in fifth convolution layer we used 0.5 dropout to overcome network Overfitting and the last layer is flatten layer which changed 2D layer to 1D with network depth of 128 final drop out of 0.25 . In our Model Hidden layers in the middle ReLu activation Function used for final prediction Softmax activation function used. Based on Our Model parameters discussed above we found as below Figure 4.3 precision, recall and F1-score.

	precision	recall	f1-score	support
Afar	0.93	1.00	0.96	140
Amhara	0.86	0.93	0.89	140
Beshangul Gumuz	0.99	1.00	0.99	140
Dawuro	1.00	0.94	0.97	140
Gambela	0.99	0.98	0.98	140
Gurage	0.98	0.92	0.95	140
Hadiya	0.99	0.94	0.96	140
Harari	0.92	0.96	0.94	140
Kambata	0.97	0.99	0.98	140
Oromoo	0.97	0.86	0.91	140
Sidama	0.99	0.98	0.98	140
Siltie	0.94	0.94	0.94	140
Somale	0.98	0.94	0.96	140
Tigrie	0.99	0.99	0.99	140
Unknown	0.86	0.91	0.89	140
Welayta	0.93	0.98	0.95	140
kaffa	0.98	0.96	0.97	140
accuracy			0.95	2380
macro avg	0.96	0.95	0.95	2380
weighted avg	0.96	0.95	0.95	2380

Figure 4. 4 Precision, recall, and F1-score

As we see above figure 4.3 we get average testing precision of 96%, Average Recall 95% and fl-score 95%. Precision tells us about FP while recall tells us about FN. Ideally FN and FP needs to zero but we found in Afar and Welayta cultural cloth performs 93% precision it means there are 7% not afar and Welayta but predicted as they are each of them, Amhara 86% precision which is there are 14 % which not belongs to Amhara but, predicted us Amhara, Beshangul Gumuz, Gambella, Hadiya Sidama, Tigre and Welayta there testing precision is 99% which is only 1% not belonging to them Predicted us them wrongly, Dawro 100% precision which means there is no other image predicted as Dawro, Gurage 98%, Somali and Kaffa 98% Precision means 2% Not belonging to them predicted as they are each of them., Harari 92% precision which is there are 8% not belonging to Harari predicted as Harari, Oromo and Kambata both 97% Precision which is there is 3% not belonging to Oromo and kambata predicted as them respectively. Siltie 94% Precision means there is 6% not belonging to siltie but predicted as siltie

Recall of Afar and Beshangul Gumuz are 100% which means there is no under Afar and Beshangul Gumuz cultural cloth category recognized as other, recall of Amhara is 93% which means there is 7% from testing Amhara cloth recognized as other, Dawro, Hadiya and Somali recall is 94% which from their testing cloth not identified as there is 6%, Gambela and Welayta recall are 98% which only 2% of their testing data not identified. Gurage recall is 92% which is 8% from their testing image not identified as Gurage, Harari and Kaffa recall is 96 which is 4% of their test image data not identified, Oromo recall is 86% which means there are 14% of Oromo testing cultural cloth not identified as Oromo cultural cloth. Finally Average sum of F1-score is 95%. See below figures 4.4 Our Model training set up to epoch 64

```
Epoch 1/64
298/298 [==============================] - 155s 499ms/step - loss: 2.1650 - accuracy: 0.3740 - val_loss: 1.3485 - val_accuracy: 0.6102
Epoch 2/64
298/298 [==============================] - 134s 451ms/step - loss: 1.3886 - accuracy: 0.5927 - val_loss: 1.2632 - val_accuracy: 0.6182
Epoch 3/64
298/298 [==============================] - 136s 456ms/step - loss: 1.1150 - accuracy: 0.6675 - val_loss: 1.0425 - val_accuracy: 0.6922
Epoch 4/64
298/298 [==============================] - 136s 455ms/step - loss: 0.9636 - accuracy: 0.7131 - val_loss: 0.8910 - val_accuracy: 0.7460
Epoch 5/64
298/298 [==============================] - 136s 458ms/step - loss: 0.8211 - accuracy: 0.7529 - val_loss: 0.9732 - val_accuracy: 0.7208
Epoch 6/64
298/298 [==============================] - 136s 457ms/step - loss: 0.7341 - accuracy: 0.7771 - val_loss: 0.7041 - val_accuracy: 0.7981
Epoch 7/64
298/298 [==============================] - 135s 455ms/step - loss: 0.6547 - accuracy: 0.7965 - val_loss: 0.7006 - val_accuracy: 0.8019
Epoch 8/64
298/298 [==============================] - 135s 454ms/step - loss: 0.5842 - accuracy: 0.8213 - val_loss: 0.6413 - val_accuracy: 0.8154
Epoch 9/64
298/298 [==============================] - 134s 451ms/step - loss: 0.5302 - accuracy: 0.8341 - val_loss: 0.7161 - val_accuracy: 0.7965
Epoch 10/64
298/298 [==============================] - 134s 449ms/step - loss: 0.4847 - accuracy: 0.8491 - val_loss: 0.7705 - val_accuracy: 0.7725
Epoch 11/64
298/298 [==============================] - 134s 450ms/step - loss: 0.4548 - accuracy: 0.8561 - val_loss: 0.7927 - val_accuracy: 0.7973
Epoch 12/64
298/298 [==============================] - 135s 455ms/step - loss: 0.4051 - accuracy: 0.8677 - val_loss: 0.5869 - val_accuracy: 0.8410
Epoch 13/64
298/298 [==============================] - 135s 453ms/step - loss: 0.3709 - accuracy: 0.8813 - val_loss: 0.6572 - val_accuracy: 0.8310
```

…

```
298/298 [==============================] - 135s 454ms/step - loss: 0.1074 - accuracy: 0.9666 - val_loss: 0.5416 - val_accuracy: 0.8919
Epoch 53/64
298/298 [==============================] - 134s 451ms/step - loss: 0.1038 - accuracy: 0.9667 - val_loss: 0.5833 - val_accuracy: 0.8818
Epoch 54/64
298/298 [==============================] - 134s 450ms/step - loss: 0.1170 - accuracy: 0.9616 - val_loss: 0.5698 - val_accuracy: 0.8839
Epoch 55/64
298/298 [==============================] - 133s 447ms/step - loss: 0.1200 - accuracy: 0.9622 - val_loss: 0.5461 - val_accuracy: 0.8869
Epoch 56/64
298/298 [==============================] - 134s 451ms/step - loss: 0.1092 - accuracy: 0.9653 - val_loss: 0.5532 - val_accuracy: 0.8776
Epoch 57/64
298/298 [==============================] - 134s 450ms/step - loss: 0.1094 - accuracy: 0.9650 - val_loss: 0.6085 - val_accuracy: 0.8726
Epoch 58/64
298/298 [==============================] - 133s 447ms/step - loss: 0.1009 - accuracy: 0.9678 - val_loss: 0.6052 - val_accuracy: 0.8860
Epoch 59/64
298/298 [==============================] - 133s 448ms/step - loss: 0.0950 - accuracy: 0.9677 - val_loss: 0.5749 - val_accuracy: 0.8835
Epoch 60/64
298/298 [==============================] - 135s 452ms/step - loss: 0.1128 - accuracy: 0.9667 - val_loss: 0.6208 - val_accuracy: 0.8696
Epoch 61/64
298/298 [==============================] - 136s 455ms/step - loss: 0.0919 - accuracy: 0.9711 - val_loss: 0.6017 - val_accuracy: 0.8793
Epoch 62/64
298/298 [==============================] - 135s 453ms/step - loss: 0.0992 - accuracy: 0.9694 - val_loss: 0.6080 - val_accuracy: 0.8919
Epoch 63/64
298/298 [==============================] - 135s 454ms/step - loss: 0.0905 - accuracy: 0.9717 - val_loss: 0.6922 - val_accuracy: 0.8696
Epoch 64/64
298/298 [==============================] - 136s 458ms/step - loss: 0.0874 - accuracy: 0.9721 - val_loss: 0.6110 - val_accuracy: 0.8915
```

Figure 4. 5 Model Training and Validation accuracy and loss

As seen on Figure 4.4 above, the accuracy of validation and training is increasing linearly as the number of epochs. The reverse is true for validation loss and accuracy lose. We get 97.21 accuracy at epoch 64 while validation accuracy is 89.15%.

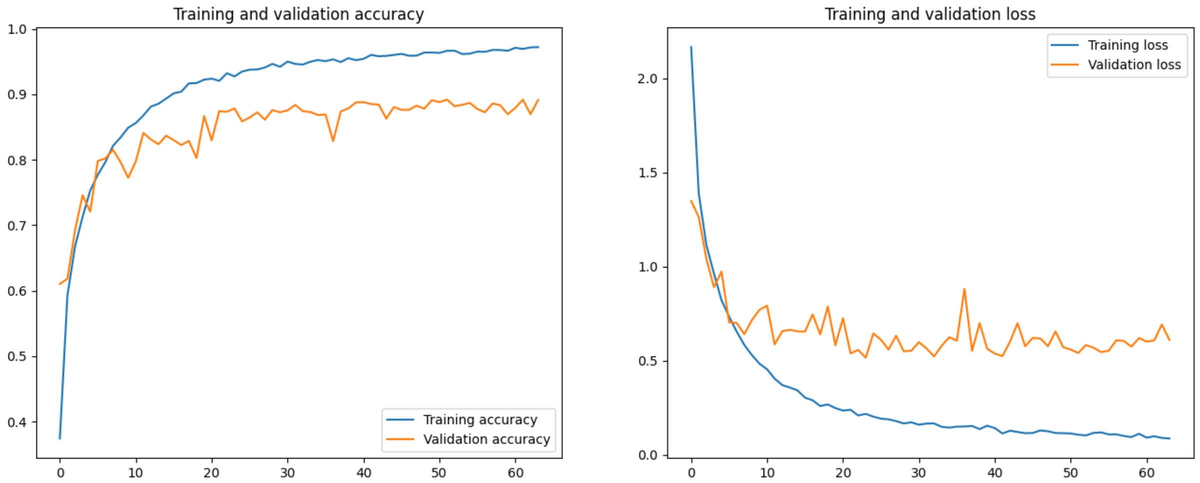

Figure 4. 6 Training versus Validation accuracy and training versus Validation Loss

As we from above graph training and validation as epoch increase accuracy increases loss decreases that means model more while epoch increased. The Gap between Validation and training seems not much. Since we used a lot of data such gap is predictable. As epoch increase network size increased and becoming Overfitting to overcome this problem early stopping the network is preferable , as a result we stopped at epoch of 64 Confusion Matrix of our model as below figure 4.6

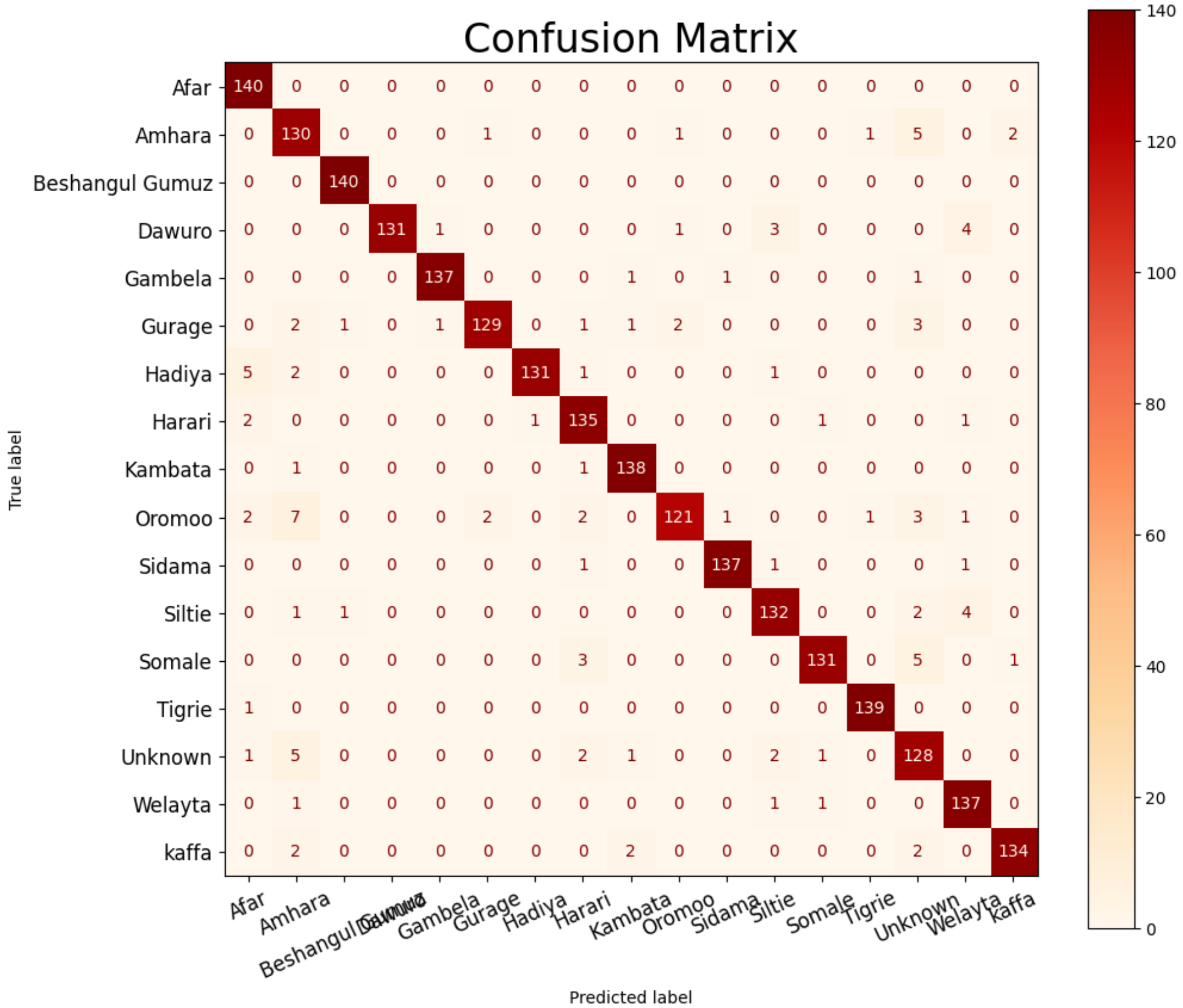

Figure 4. 7 predicted and True Level out of each class 140

The predicted and True Level out of each class 140 , Afar and Beshangul Gumuz predicts all 140 testing image data correctly, Amhara 130 image from testing of 140 cloth predicts correctly 130 image while wrongly predicts 5 image as unknown , 2 image as Kaffa cultural cloth, one image each Oromo, Gurage and Tigre. Dawro predicts from testing 140 images 131 image correctly one image categorized as Gambela one image as kambata three images as siltie and four images as Welayta. Gambela cultural cloth predicts from testing image of 140 image 137 image correctly wrongly one-one each as kambata, Sidama and siltie Gurage cultural cloth predicted correctly from out of testing data set 140 it predicts correctly 129 out of them two image classified as Amhara, one-one each Beshangul Gumuz, Gambela, Harari, Kambata, two images identified as Oromo and other three images as unknown. Hadiya

Cultural cloth from out of image 140 it predicts 131 other Five image as Afar, two images as Amhara, Harari and siltie each one-one. Harari cultural cloth from testing out of 140 images it predicts correctly 135 images other five images identified as other two images as Afar, Hadiya, Somali and Welayta each one-one. Kambata cultural cloth from out of 140 image it identified 138 image correctly while two image identified wrongly as others one-one as Amhara and Harari. Oromo cultural cloth identifies from out of 140 images 121 images correctly while other 19 image predicted wrongly two image as Afar, Seven images as Amhara, two images each as Gurage, and Harari, and Sidama, Tigre and Welayta each one-one, three predicted as unknown. Sidama cultural cloth identifies from out of testing image 140 it predicts correctly 137 other three predicted as other each one-one Harari, Siltie and Welayta. Siltie Cultural clothing predicts from out of testing image 140 it predicts correctly 132 image while other eight image predicts as other wrongly one-one predicted as Amhara and Beshangul-Gumuz other two unknown and four as Welayta. Somali Cultural cloth from testing image out of 140 it predicts correctly 131 other nine predicts as other three images as Harari, Five images as unknown and one image as Kaffa. Tigre Cultural clothing identifies from out of testing image of 140 images it predicts 139 image correctly while one image predicts as Afar cultural cloth. Welayta cultural cloth predicts from total testing image 140 it predicts correctly 137 image while other three predicts wrongly as one-one each as Somali, siltie and Amhara. Kaffa cultural clothing classifies from total testing image of 140 it predicts correctly 134 images while other six predicts as other two-two each unknown, Amhara and Kambata. Generally Our Model Predicts correctly whatever there is Noise or Image wrongly classified, Our model hits Training accuracy of 91.15% and precision accuracy of 96%

Figure bellow shows actual and predicted

Figure 4. 8 Actual Labelled and predicted

4.5 Experiment of end to end CNN with Seven Convulation Architecture

Adding in middle network two Convulation layer from previous five Convulation layers CNN end layer fully connected layers network depth 96 and 64 as bellow table 4.2

parameters we get accuracy of 93.52 and validation accuracy of 86.09 which is less than five Convulation layers.

Table 4. 2 Summery of CNN with Five Convulation architecture

Layers	Layers parameter	Activation
Conv2D	32, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	64, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	64, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	96, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	64, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	96, size(3,3)	ReLU
Max pooling	Size(2,2)	
Batchnormalization		
Conv2D	32, size(3,3)	ReLU
Max pooling	Size(2,2)	
Dropout R	0.5	Relu
Batchnormalization		
Flatten	128	
Dropout	0.25	Relu
Dense	128	
Dense	17	Softmax

```
Epoch 1/64
298/298 [==============================] - 156s 504ms/step - loss: 2.5266 - accuracy: 0.2055 - val_loss: 2.2493 - val_accuracy: 0.3111
Epoch 2/64
298/298 [==============================] - 133s 447ms/step - loss: 2.0771 - accuracy: 0.3655 - val_loss: 1.8419 - val_accuracy: 0.4288
Epoch 3/64
298/298 [==============================] - 134s 450ms/step - loss: 1.8101 - accuracy: 0.4525 - val_loss: 1.8084 - val_accuracy: 0.4569
Epoch 4/64
298/298 [==============================] - 133s 447ms/step - loss: 1.6129 - accuracy: 0.5106 - val_loss: 1.3782 - val_accuracy: 0.6284
Epoch 5/64
298/298 [==============================] - 132s 442ms/step - loss: 1.4986 - accuracy: 0.5474 - val_loss: 1.2531 - val_accuracy: 0.6389
Epoch 6/64
298/298 [==============================] - 133s 446ms/step - loss: 1.3600 - accuracy: 0.5947 - val_loss: 1.1716 - val_accuracy: 0.6469
Epoch 7/64
298/298 [==============================] - 133s 448ms/step - loss: 1.2620 - accuracy: 0.6214 - val_loss: 1.1758 - val_accuracy: 0.6599
Epoch 8/64
298/298 [==============================] - 134s 449ms/step - loss: 1.1737 - accuracy: 0.6509 - val_loss: 0.8875 - val_accuracy: 0.7549
```

…

```
298/298 [==============================] - 134s 451ms/step - loss: 0.2315 - accuracy: 0.9242 - val_loss: 1.1659 - val_accuracy: 0.7579
Epoch 59/64
298/298 [==============================] - 134s 450ms/step - loss: 0.2982 - accuracy: 0.9083 - val_loss: 0.7269 - val_accuracy: 0.8441
Epoch 60/64
298/298 [==============================] - 135s 452ms/step - loss: 0.2337 - accuracy: 0.9268 - val_loss: 0.9322 - val_accuracy: 0.7995
Epoch 61/64
298/298 [==============================] - 136s 458ms/step - loss: 0.2328 - accuracy: 0.9295 - val_loss: 0.6684 - val_accuracy: 0.8550
Epoch 62/64
298/298 [==============================] - 136s 458ms/step - loss: 0.2236 - accuracy: 0.9274 - val_loss: 0.6857 - val_accuracy: 0.8537
Epoch 63/64
298/298 [==============================] - 136s 457ms/step - loss: 0.2330 - accuracy: 0.9250 - val_loss: 0.7293 - val_accuracy: 0.8415
Epoch 64/64
298/298 [==============================] - 136s 456ms/step - loss: 0.2047 - accuracy: 0.9352 - val_loss: 0.6447 - val_accuracy: 0.8609
```

Figure 4. 9 Model Training and Validation accuracy and loss

Testing phase of this model average precision accuracy of 92 as below figure 4.9 below is less than when compared with five Convulation layers

	precision	recall	f1-score	support
Afar	0.93	0.99	0.96	140
Amhara	0.82	0.84	0.83	140
Beshangul Gumuz	0.96	0.95	0.96	140
Dawuro	0.98	0.93	0.96	140
Gambela	0.92	0.99	0.95	140
Gurage	0.93	0.87	0.90	140
Hadiya	0.93	0.91	0.92	140
Harari	0.96	0.88	0.92	140
Kambata	0.97	0.99	0.98	140
Oromoo	0.85	0.81	0.83	140
Sidama	0.98	0.88	0.92	140
Siltie	0.90	0.92	0.91	140
Somale	0.94	0.89	0.92	140
Tigrie	0.94	1.00	0.97	140
Unknown	0.70	0.93	0.80	140
Welayta	0.98	0.87	0.92	140
kaffa	0.99	0.94	0.96	140
accuracy			0.92	2380
macro avg	0.92	0.92	0.92	2380
weighted avg	0.92	0.92	0.92	2380

Figure 4. 10 Precision, recall, and F1-score

4.6 Experiment of end to end CNN with three Convulation Architecture

With three Convulation Layers with network depth first Convulation layers 32, second Convulation 64 and third Convulation 32 with each Convulation with dropout of 50% to minimize network Overfitting and with last layer fully connected layers.

Table 4. 3 Summery of CNN with three Convulation architecture

Layers	Layers parameter	Activation
Conv2D	32, size(3,3)	ReLU
Max pooling	Size(2,2)	
Dropout	0.5	Relu
Batchnormalization		
Conv2D	64, size(3,3)	ReLU
Max pooling	Size(2,2)	
Dropout	0.5	Relu
Batchnormalization		
Conv2D	32, size(3,3)	ReLU
Max pooling	Size(2,2)	
Dropout R	0.5	ReLu
Batchnormalization		
Flatten	128	
Dropout	0.5	ReLu
Dense	128	
Dense	17	Softmax

Final accuracy at epoch 64 as figure 4.10 below with parameter similar with we used in seven and five Convulation architecture we get training accuracy of 94.47 and Val accuracy 83.82

```
Epoch 1/64
298/298 [==============================] - 151s 504ms/step - loss: 2.5101 - accuracy: 0.2765 - val_loss: 2.2534 - val_accuracy: 0.3592
Epoch 2/64
298/298 [==============================] - 136s 455ms/step - loss: 1.9492 - accuracy: 0.4070 - val_loss: 1.9074 - val_accuracy: 0.4265
Epoch 3/64
298/298 [==============================] - 134s 449ms/step - loss: 1.7170 - accuracy: 0.4845 - val_loss: 1.8365 - val_accuracy: 0.4408
Epoch 4/64
298/298 [==============================] - 133s 445ms/step - loss: 1.5295 - accuracy: 0.5383 - val_loss: 1.5071 - val_accuracy: 0.5832
Epoch 5/64
298/298 [==============================] - 133s 444ms/step - loss: 1.3751 - accuracy: 0.5869 - val_loss: 1.2940 - val_accuracy: 0.6349
Epoch 6/64
298/298 [==============================] - 132s 442ms/step - loss: 1.2594 - accuracy: 0.6189 - val_loss: 1.2282 - val_accuracy: 0.6391
Epoch 7/64
298/298 [==============================] - 131s 439ms/step - loss: 1.1466 - accuracy: 0.6511 - val_loss: 1.2795 - val_accuracy: 0.6311
Epoch 8/64
```

…

```
Epoch 56/64
298/298 [==============================] - 134s 449ms/step - loss: 0.2131 - accuracy: 0.9306 - val_loss: 0.7950 - val_accuracy: 0.8126
Epoch 57/64
298/298 [==============================] - 134s 449ms/step - loss: 0.2040 - accuracy: 0.9350 - val_loss: 0.6903 - val_accuracy: 0.8361
Epoch 58/64
298/298 [==============================] - 136s 454ms/step - loss: 0.2129 - accuracy: 0.9315 - val_loss: 0.8389 - val_accuracy: 0.8294
Epoch 59/64
298/298 [==============================] - 136s 455ms/step - loss: 0.2133 - accuracy: 0.9321 - val_loss: 0.6976 - val_accuracy: 0.8290
Epoch 60/64
298/298 [==============================] - 136s 455ms/step - loss: 0.1942 - accuracy: 0.9379 - val_loss: 0.7351 - val_accuracy: 0.8294
Epoch 61/64
298/298 [==============================] - 134s 448ms/step - loss: 0.2004 - accuracy: 0.9375 - val_loss: 0.6857 - val_accuracy: 0.8462
Epoch 62/64
298/298 [==============================] - 137s 458ms/step - loss: 0.2004 - accuracy: 0.9330 - val_loss: 0.7432 - val_accuracy: 0.8324
Epoch 63/64
298/298 [==============================] - 136s 456ms/step - loss: 0.1863 - accuracy: 0.9374 - val_loss: 0.7354 - val_accuracy: 0.8382
Epoch 64/64
298/298 [==============================] - 137s 457ms/step - loss: 0.1771 - accuracy: 0.9447 - val_loss: 0.8081 - val_accuracy: 0.8382
```

Figure 4. 11 Model Training and Validation accuracy and loss

From testing phase as below figure 4.11 accuracy macro average precision, recall 0.93.and f1-score are 93%

	precision	recall	f1-score	support
Afar	0.93	0.99	0.96	140
Amhara	0.83	0.90	0.87	140
B.Gumuz	0.96	0.99	0.97	140
Dawuro	0.99	0.88	0.93	140
Gambela	0.92	0.99	0.95	140
Gurage	0.90	0.91	0.90	140
Hadiya	0.93	0.92	0.93	140
Harari	0.88	0.97	0.92	140
Kambata	0.95	0.98	0.96	140
Oromoo	0.90	0.84	0.87	140
Sidama	0.96	0.93	0.95	140
Siltie	0.96	0.86	0.91	140
Somale	0.98	0.89	0.93	140
Tigrie	0.99	0.99	0.99	140
Unknown	0.81	0.95	0.87	140
Welayta	0.98	0.87	0.92	140
kaffa	0.97	0.94	0.95	140
accuracy			0.93	2380
macro avg	0.93	0.93	0.93	2380
weighted avg	0.93	0.93	0.93	2380

Figure 4. 12 Precision, recall, and F1-score

4.7 Comparison of conducted experiments

Comparing with CNN with three, five and seven Convulation layer we get high accuracy with parameters with five Convulation we get training accuracy of 97.21 and validation accuracy of 89.15 while in architecture with three Convulation we get 94.47 training accuracy and validation accuracy of 83.82 , in seven Convulation architecture we get training accuracy of 93.52 and validation accuracy of 86.09

Table 4. 4 CNN Architecture comparison

NO:	CNN Architecture	Training accuracy	Validation accuracy
1	Three Convulation	94.47	83.82
2	Five Convulation	97.21	89.15
3	Seven Convulation	93.52	86.09

As Above table 4.4 we get high accuracy while using CNN architecture with Five Convulation reach training accuracy of 97.21

CHAPTER FIVE

CONCLUTION AND RECOMMENDATION

5.1 Conclusion

Ethiopian is known by different cultural clothing style worn in ceremonial occasion. There are different Ethiopian Cultural clothing style based on color, design and fabrics, to predict such different cultural clothing style with human vision is difficult and needs human experts to identify to which it belongs. Different Ethiopian cultural clothing collected from Ethiopian Minister of Culture and Tourism, from Oromo cultural center and from regional mass media and their cultural center's websites and some cultural images captured on exhibition and cultural shops. We gathered total image of 11,200 for each 16 classes 700 images. To identify Ethiopian cultural cloth without human experts there need to be developing model. After compared CNN with three, five and seven Convulation layers we get high training accuracy 97.21 and Validation accuracy 89.15 when we use CNN with five Convulation. After a thorough review of literature and related works, we have identified that the identification of Cloth fabrics is given less emphasis and are unresolved problems yet.so, This model minimize time consumed by customer and it helps peoples to focus on their cultural cloth to develop further.

5.2 Recommendation

This research can help with cultural cloth identifications and categorization under Ethiopia. We categorize based on area majority inhabitants other researcher may get into details since there is above 16 cultural cloth styles in Ethiopia and design fabrics. This model used for other researches too on image identification's a result; this study can recommend future researchers to apply the study's findings in the above-mentioned domains, as well as other areas where cultural cloth is used.

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Appendix

Preprocessing image and resizing

```
Image_data ="../content/drive/MyDrive/image_data/training data"
img_height= 224 #to resizing image data into equal 224x224
img_width = 224
batch_size = 32
```

Training Data 20% of image data

```
Train_data = tf.keras.utils.image_dataset_from_directory(
             Image_data
            validation_split=0.2, #splitting image data 80% to training
             subset= 'training',
             seed = 123,
             image_size=(img_height,img_width),
             batch_size=batch_size
)
```

Validation Data 20% of image data

```
val_data = tf.keras.utils.image_dataset_from_directory(
      Image_data,
       validation_split=0.2, #splitting image data 20%
       subset="validation",
       seed=123,
       image_size=(img_height,img_width),
       batch_size=batch_size
)
```

Model proposed

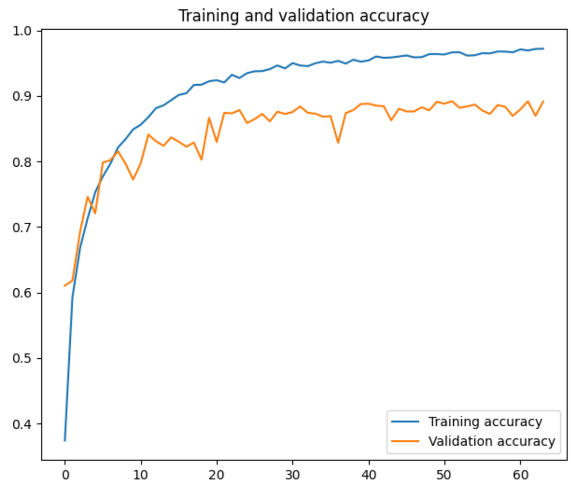
```
model = Sequential() #sequential layer chnaging image into Layers 2D
model.add(Conv2D(32, kernel_size = (3, 3),padding="same",
activation='relu', input_shape=(img_height,img_width ,3)))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(BatchNormalization())
model.add(Conv2D(64, kernel_size=(3,3),padding="same",
activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(BatchNormalization())
```

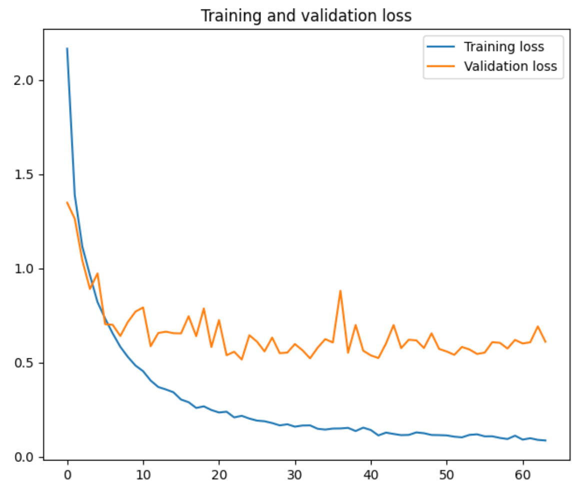
```
model.add(Conv2D(64, kernel_size=(3,3),padding="same",
activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(BatchNormalization())
model.add(Conv2D(96, kernel_size=(3,3),padding="same",
activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(BatchNormalization())
model.add(Conv2D(32, kernel_size=(3,3),padding="same",
activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.5)) #50% dropout
model.add(BatchNormalization())
model.add(Flatten()) #Flatten Layer changing 2D inf to 1D
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.25))  #25% dropout
model.add(Dense(num_classes,activation='Softmax')) #End layer with
Softmax activation
```

Testing Data 20% of image data

```
test_image _data = "../content/drive/MyDrive/culture/CULTURE"
test_data_ds = tf.keras.utils.image_dataset_from_directory(test_image
_data,
           seed = 123,
            image_size=(img_height,img_width),
            shuffle=False
)
```

Graph Validation versus training





Training phase epoch

```
Epoch 1/64
298/298 [==============================] - 155s 499ms/step - loss: 2.1650 - accuracy: 0.3740 - val_loss: 1.3485 - val_accuracy: 0.6102
Epoch 2/64
298/298 [==============================] - 134s 451ms/step - loss: 1.3886 - accuracy: 0.5927 - val_loss: 1.2632 - val_accuracy: 0.6182
Epoch 3/64
298/298 [==============================] - 136s 456ms/step - loss: 1.1150 - accuracy: 0.6675 - val_loss: 1.0425 - val_accuracy: 0.6922
Epoch 4/64
298/298 [==============================] - 136s 455ms/step - loss: 0.9636 - accuracy: 0.7131 - val_loss: 0.8910 - val_accuracy: 0.7460
Epoch 5/64
298/298 [==============================] - 136s 458ms/step - loss: 0.8211 - accuracy: 0.7529 - val_loss: 0.9732 - val_accuracy: 0.7208
Epoch 6/64
298/298 [==============================] - 136s 457ms/step - loss: 0.7341 - accuracy: 0.7771 - val_loss: 0.7041 - val_accuracy: 0.7981
Epoch 7/64
298/298 [==============================] - 135s 455ms/step - loss: 0.6547 - accuracy: 0.7965 - val_loss: 0.7006 - val_accuracy: 0.8019
Epoch 8/64
298/298 [==============================] - 135s 454ms/step - loss: 0.5842 - accuracy: 0.8213 - val_loss: 0.6413 - val_accuracy: 0.8154
Epoch 9/64
298/298 [==============================] - 134s 451ms/step - loss: 0.5302 - accuracy: 0.8341 - val_loss: 0.7161 - val_accuracy: 0.7965
Epoch 10/64
298/298 [==============================] - 134s 449ms/step - loss: 0.4847 - accuracy: 0.8491 - val_loss: 0.7705 - val_accuracy: 0.7725
Epoch 11/64
298/298 [==============================] - 134s 450ms/step - loss: 0.4548 - accuracy: 0.8561 - val_loss: 0.7927 - val_accuracy: 0.7973
Epoch 12/64
298/298 [==============================] - 135s 455ms/step - loss: 0.4051 - accuracy: 0.8677 - val_loss: 0.5869 - val_accuracy: 0.8410
Epoch 13/64
298/298 [==============================] - 135s 453ms/step - loss: 0.3709 - accuracy: 0.8813 - val_loss: 0.6572 - val_accuracy: 0.8310
```

…

```
298/298 [==============================] - 135s 454ms/step - loss: 0.1074 - accuracy: 0.9666 - val_loss: 0.5416 - val_accuracy: 0.8919
Epoch 53/64
298/298 [==============================] - 134s 451ms/step - loss: 0.1038 - accuracy: 0.9667 - val_loss: 0.5833 - val_accuracy: 0.8818
Epoch 54/64
298/298 [==============================] - 134s 450ms/step - loss: 0.1170 - accuracy: 0.9616 - val_loss: 0.5698 - val_accuracy: 0.8839
Epoch 55/64
298/298 [==============================] - 133s 447ms/step - loss: 0.1200 - accuracy: 0.9622 - val_loss: 0.5461 - val_accuracy: 0.8869
Epoch 56/64
298/298 [==============================] - 134s 451ms/step - loss: 0.1092 - accuracy: 0.9653 - val_loss: 0.5532 - val_accuracy: 0.8776
Epoch 57/64
298/298 [==============================] - 134s 450ms/step - loss: 0.1094 - accuracy: 0.9650 - val_loss: 0.6085 - val_accuracy: 0.8726
Epoch 58/64
298/298 [==============================] - 133s 447ms/step - loss: 0.1009 - accuracy: 0.9678 - val_loss: 0.6052 - val_accuracy: 0.8860
Epoch 59/64
298/298 [==============================] - 133s 448ms/step - loss: 0.0950 - accuracy: 0.9677 - val_loss: 0.5749 - val_accuracy: 0.8835
Epoch 60/64
298/298 [==============================] - 135s 452ms/step - loss: 0.1128 - accuracy: 0.9667 - val_loss: 0.6208 - val_accuracy: 0.8696
Epoch 61/64
298/298 [==============================] - 136s 455ms/step - loss: 0.0919 - accuracy: 0.9711 - val_loss: 0.6017 - val_accuracy: 0.8793
Epoch 62/64
298/298 [==============================] - 135s 453ms/step - loss: 0.0992 - accuracy: 0.9694 - val_loss: 0.6080 - val_accuracy: 0.8919
Epoch 63/64
298/298 [==============================] - 135s 454ms/step - loss: 0.0905 - accuracy: 0.9717 - val_loss: 0.6922 - val_accuracy: 0.8696
Epoch 64/64
298/298 [==============================] - 136s 458ms/step - loss: 0.0874 - accuracy: 0.9721 - val_loss: 0.6110 - val_accuracy: 0.8915
```

Predicted image