Telediagnosticstics: An Automatic Biomedical Image Matching and Retrieval in a Multi-distributed Telecommunications Environment in Kenya

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Abstract

Diagnostic images are progressively being used within healthcare institutions for diagnosis, treatment guidance planning and disease progression monitoring. Effective management of medical cases can be costly and requires reliable patient diagnosis performed by a trained physician. As a rule of thumb, the identification of an image involves matching of features extracted from the image with a pre stored original pattern. The study uses a computerized method of segmentation and classification of medical images using artificial intelligence algorithms such as fuzzy logics to automatically match and compute similarity indexes for biomedical images sourced from digital sources such as digital microscopes.

Relevance to innovation. A new innovative process design integrated into a clinically testable telemedicine tool assembled from existing resources with a view to addressing the Kenya ehealth strategy anchored on Vision 2030.

Key Words. Artificial intelligence, biomedical images, pattern matching, telediagnostics, telemedicine

INTRODUCTION

Not so well equipped medical centers that operate seldom have the expected medical practitioners that can run them. It therefore becomes quite obvious that whenever an outbreak of a disease occurs, doctors are flown to the affected parts of the county on emergency mode. It is also notable that there are quite very few referral hospitals across the country and area concentrated in urban centers. This implies that rural areas have lesser number of good doctors and therefore this leaves a greater population percentage in the countryside with less specialist services. As per the ehealth strategy report 2011-2017, 80% of clinicians serve 20% of the population and the world health organization 2016 report on telehealth programs in Kenya indicates that, the questions on teleradiology, teledermatology, telepathology, telepsychiatry and remote patient monitoring were never answered by Kenya government as per Table 1.
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Table 1: Telehealth Programmes Country Overview: Telemedicine Response by Kenya by World health Organization, 2016

<table>
<thead>
<tr>
<th>Health system level</th>
<th>Programme type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teleradiology</td>
<td>Local: NA</td>
</tr>
<tr>
<td>Teledermatology</td>
<td>Informal: NA</td>
</tr>
<tr>
<td>Telepsychiatry</td>
<td>NA</td>
</tr>
<tr>
<td>Telepathology</td>
<td>NA</td>
</tr>
<tr>
<td>Remote patient monitoring</td>
<td>NA</td>
</tr>
</tbody>
</table>

Legend

- Indicates question was unanswered

Local or peripheral level – health posts, health centers providing basic level of care

Informal – use of ICT for health purposes in the absence of formal processes and policies

MAIN OBJECTIVE

The main objective was to develop and demonstrate a testable prototype of a biomedical image pattern matching tool using artificial intelligence techniques that could efficiently retrieve, match and predict similarity of biomedical visual images from digital sources such as USB microscope or digital microscopes as input devices. Then use multimodal database techniques of the captured specimen images of a patient blood, stool, or skin samples for diagnosis based on artificial intelligence algorithms.

The main objective was realized through the following sub-objectives:

1. Utilization of existing technologies such as the Global System for Mobile Communication (GSM) network and internet to deliver efficient and effective telediagnostics tool that was used to test sample image specimen.
2. Evaluation of various digital image compression techniques or image formats for optimum medical images transmission and storage mechanisms. Whilst checking if the image compression algorithm has an effect on distortion levels.

LITERATURE REVIEW

Since its inception, mobile phones have become indispensable in people’s daily life for communication, data capture and media exchange. Providing multimedia capabilities has been one of the biggest improvements in mobile telephony and with various camera phones providing multimedia capturing, browsing, editing, and sharing. The coming of third generation (3G), 4G and 5G networks with fiber optics networks are all engineered for faster and more reliable internet access throughputs.

We intend to tap on such high end technology solve or lessen some of the human burdens such as on time diagnostics of simple ailments. This study and by far such inventions could be used to provide speedy information to gather statistics on diseases. Computer scientists have a duty to champion the domain knowledge by collaborating with various domain experts such medicine, agriculture, and biology. Early and accurate diagnosis of the nature of parasites has always been made with a microscope, which is essential and crucial for appropriate choice of remedial drugs.

As similar research has been conducted by the University of California, Berkeley where they developed a mobile telephone with an inbuilt microscope. The device is a sophisticated mobile microscope with an advanced digital camera to capture microphotographs of the blood smear. The captured image is sent to specialists for observation. It is the intention of this project to transmit the digitized image to a pattern matching application for automatic diagnosis. Figure 1, is an image grab from a Nokia mobile phone turned into microscope.
The device will enable health workers in remote, rural areas to take high resolution images of a patient's blood cells using a cell-phone camera, and then transmit the photos for diagnosis online as per University of California, Berkeley study.

The computerized biomedical tool advanced by this research will processes the information contained in the image data and create an abstraction of its content in terms of visual attributes. Subsequent analysis and retrievals of the image will be dealt with solely as abstraction rather than with the image itself. Any image inserted into the database is analyzed and a compact representation of its content is stored in a feature vector or signature location.

Using artificial intelligence (AI) techniques, the signature of the image in is extracted by segmenting the image into regions. Each region is associated with its color, texture, and shape information. The signature has a region-based information along with global color, texture, and shape information to represent the attributes for the entire image. The images will be matched based on color, texture, and shape attributes. The positions of these visual attributes of the image are represented by a location.

The Electromagnetic Spectrum – The color wavelength visible to the human eye ranges from 4000 to 7000 angstroms. This is similar to an electromagnetic radiation with wavelengths between about 380 and 700 nanometers. This radiation is known as light. The visible spectrum and electromagnetic radiation are illustrated below in Figure 3.

Effects of light on pictures - The eye has three classes of color sensitive light receptors called cones, which respond roughly to red, blue and green light (around 650, 530 and 460 nm, respectively). A range of colors can be reproduced by one of two complimentary approaches
additive and subtractive color. Additive color combines light sources, starting with darkness (black). The additive primary colors are red (R), green (G), and blue (B). Adding R and G light makes yellow (Y). Similarly, G + B = cyan (C) and R + B = magenta (M). Combining all three additive primaries makes white. Subtractive color illuminates objects that contain dyes or pigments that remove portions of the visible spectrum. The objects may either transmit light (transparencies) or reflect light. The subtractive primaries are C, M and Y. Cyan absorbs red; hence C is sometimes called "minus red" (-R). Similarly, M is -G and Y is -B.

In determining the image similarities, color histogram is one method used. It represents an image by breaking down the various color components of an image and graphs out the occurrences and intensity of each color. Then to compare the two images, one needs only to compare the color histograms of the two images and determine the similarity of the two histograms. Another approach for color comparison is color correlogram (scatter plots) method. This method of comparison does not take into account space information. That is, the space or distance between one color and another color, but solves the issue of integration of spatial information into color histograms.

Texture is another key component of an image. It is the perception of smoothness or coarseness of an object. Similar to the color histogram, many of the current techniques for image texture analysis lack the spatial information allowing one to compare the location of a coarse object within an image and a smooth object. Methodologies such as Gabor filters can be used. Gabor functions when applied to an image, converts image texture components into graphs. Gabor filters allow one to quantify the coarseness or smoothness of an image. The comparison of the images is performed against the mathematical representation of the graphs. This enables content based image retrieval systems to compare the textures of two different images.

Shape features are usually described after the images have already been segmented or broken out. A good shape representation of an image should handle changes in translation, rotation, and or scaling. This is rather difficult to achieve as the images involve numerous geometric shapes that when numerically characterized, will typically lose information.

Weight values can be between 0.0 and 1.0 and during processing, the values are normalized such that they total 1.0. The weight of at least one of the color, texture, or shape attributes
must be set to greater than zero. Score: The similarity measure for each visual attribute is calculated as the score or distance between the two images with respect to that attribute. The score can range from 0.00 (no difference) to 100.0 (maximum possible difference). Thus, the more similar the two images are with respect to a visual attribute, the smaller the score will be for that attribute.

As an example of how distance is determined, assume that the dots in Figure 4 below represent scores for three images with respect to two visual attributes, such as color and shape, plotted along the x-axis and y-axis of a graph. The application image matching process ensures that image signatures are generated. The score is the relative distance between two images being compared. The score for each attribute is used to determine the degree of similarity when images are compared, with a smaller distance reflecting a closer match.

As an illustration for matching, assume Image 1 is the comparison image, and Image 2 and Image 3 are each being compared with Image 1. With respect to the x-axis and y-axis, the distance between Image 1 and Image 2 is relatively small whereas the distance between Image 1 and Image 3 is much greater. Thus when images are matched, the degree of similarity depends on a weighted sum reflecting the weight and distance of all three of the visual attributes in conjunction with location of the comparison image and the test image.

5.1 METHODOLOGY

The study design involved software modeling and prototyping the biomedical imaging tool using a standard software development life cycle model. The design and integration of interface tools on a multimodal distributed communication architecture as per Figures 5 and 6. The testing and tuning of the tool involved acquiring diagnostic images from reliable sources for research. However, clinical trial and calibration of the tool was out of scope.

The biomedical tool is designed to fit into the overall clinical roadmap for clinical data generation in Figure 7, for natural language processing data enrichment, machine learning data analytics and clinical decision making using electronic medical records (EMR) and electrophysiological (EP). The road map starts and ends with clinical activities.
DISCUSSION

While the evaluation of the digital image compression techniques for optimum transmission and storage was analyzed, the two mostly used image compression algorithms the study came across are lossy and lossless (Table 2). Lossy means that the decompressed image loses some of the information, but the only information that is judged to be insignificant is left. While lossless means they preserve all the original information of the image.

The goal of data compression is to represent the data in a way that reveals some redundancy. We may think of the color of each pixel as represented by a three dimensional vector (R, G, B) consisting of its red, green, and blue components. In a typical image, there is a significant amount of correlation between these components. For this reason, we will use a color space transform to produce a new vector whose components represent luminance, Y, and blue and red chrominance, C_b and C_r.

Digital images such as photographs are generally encoded as rows and columns of pixels (from picture elements). This type of image format is called a raster image. It has been found that, the more the pixels in each row and column, the better the resolution of the image. An image with 24 bits of color information for each pixel will generally look better than an image with only 16 bits of color information for each pixel.

Experimental analysis of similar biomedical image sample data with various image compressions algorithms

A malaria parasite image obtained from center for disease control (CDC) website was compressed into five different image compression algorithms with extension .png, .bmp, .jpg, .tif and .gif. The objective of successful medical imaging technology is the ability to minimize image storage size in order to speed up image data transmission and reduce storage cost.

The experimental procedure for image compression algorithms test was done using this biomedical image tool and the results shows that, out of the five compression methods, all of them gave different computational results as shown in Table 3. It is good to note that .tif and .gif gave different similarity index score (0.012 and 3.26228) of the same image with expected
similarity index of zero. We can therefore conclude that the image compression algorithm has a direct correlation on storage size and image distortion level.

Table 2: Various Image compression comparison table

<table>
<thead>
<tr>
<th>Format</th>
<th>Extension</th>
<th>C or U</th>
<th>Lossy or Lossless</th>
<th>Geo-aware</th>
<th>Suitable for large image</th>
<th>Proprietary or open</th>
</tr>
</thead>
<tbody>
<tr>
<td>BBB</td>
<td>.bil, .bip,.bsq</td>
<td>U</td>
<td>Lossless</td>
<td>Yes</td>
<td>Yes</td>
<td>Open</td>
</tr>
<tr>
<td>GeoTIFF-raw</td>
<td>.tif</td>
<td>U</td>
<td>Lossless</td>
<td>Yes</td>
<td>Yes, up to 2GB</td>
<td>Open</td>
</tr>
<tr>
<td>GeoTIFF-LZW</td>
<td>.tif</td>
<td>C</td>
<td>Lossless</td>
<td>Yes</td>
<td>Yes, up to 2GB</td>
<td>Open</td>
</tr>
<tr>
<td>PNG</td>
<td>.png</td>
<td>C</td>
<td>Both</td>
<td>No</td>
<td>No</td>
<td>Open</td>
</tr>
<tr>
<td>GeoTIFF-jpeg</td>
<td>.tif</td>
<td>C</td>
<td>Lossy</td>
<td>Yes, up to 2GB</td>
<td>Yes, up to 2GB</td>
<td>Open</td>
</tr>
<tr>
<td>jpg</td>
<td>.jpg</td>
<td>C</td>
<td>Lossy</td>
<td>No</td>
<td>No</td>
<td>Open</td>
</tr>
</tbody>
</table>

U-Uncompressed  C-Compressed
Table 3: Image compression comparison score of similarity for image distortion level

<table>
<thead>
<tr>
<th>Specimen Name</th>
<th>Width (pixels)</th>
<th>Height (pixels)</th>
<th>Length (bytes)</th>
<th>Score</th>
<th>File size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compress.png</td>
<td>748</td>
<td>504</td>
<td>436164</td>
<td>0</td>
<td>426Kb</td>
</tr>
<tr>
<td>Compress.bmp</td>
<td>748</td>
<td>504</td>
<td>1131030</td>
<td>0</td>
<td>1,105Kb</td>
</tr>
<tr>
<td>Compress.jpg</td>
<td>748</td>
<td>504</td>
<td>26553</td>
<td>0</td>
<td>26Kb</td>
</tr>
<tr>
<td>Compress.tif</td>
<td>748</td>
<td>504</td>
<td>701788</td>
<td>0.012</td>
<td>686Kb</td>
</tr>
<tr>
<td>Compress.gif</td>
<td>748</td>
<td>504</td>
<td>61326</td>
<td>3.26228</td>
<td>60Kb</td>
</tr>
</tbody>
</table>

Figure 8: The diagnostic imaging demand data types considered in the artificial intelligence

Automatic Biomedical Image analysis in a multi-distributed telecommunications environment design and outputs for efficient and effective

While physical examination notes and laboratory results are the main data sources, we point out that with image data with clinical notes contain large portions of unstructured narrative texts that are not directly analyzable. Consequently, any artificial intelligence applications focus on first converting the unstructured text to machine understandable electronic medical record (EMR). Karakülah et al used artificial intelligence technologies to extract phenotypic features from case reports to enhance the diagnosis accuracy of the congenital anomalies.

The diagnostic imaging shows a steady trend in the demand for biomedical image tools and technologies as shown in Figure 8. This study however did not go into the unstructured text feature extraction, but limited itself to similarity computation of biomedical images. There two schools of thought with regards to digital imagery studies. One is the machine learning (ML) techniques that analyses structured data, such as imaging. The second one is natural language processing (NLP) method, which extracts information from unstructured data such as clinical notes or medical journals to supplement and enrich structured medical data.

The application is accessible online once hosted with a user interface and the administrator consoles. After a health worker or user logs in, they will be able to navigate the diseases upload screens for specimen testing per Figures 9 and 10.

Once the upload is done, an SMS report will be delivered only to the registered health worker or user as shown in Figure 11. Figure 12, gives a summary report that can be spooled online from the biomedical tool directly via web page.
Figure 9: Login Screen

Figure 10: Specimen uploading screen for Malaria specimens

Figure 11: SMS report relayed on registered mobile phone

Figure 12: Web interface report

<table>
<thead>
<tr>
<th>Specimen Name</th>
<th>Width</th>
<th>Height</th>
<th>Length</th>
<th>Score</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>m_Original_copy.jpg</td>
<td>253</td>
<td>247</td>
<td>5203</td>
<td>0</td>
<td>The Specimen Closely Matches the Parasite. Malaria Found</td>
</tr>
<tr>
<td>m_alloy_69045678.jpg</td>
<td>256</td>
<td>259</td>
<td>4487</td>
<td>3.6937</td>
<td>The Specimen Closely Matches the Parasite. Malaria Found</td>
</tr>
<tr>
<td>m_tom_12345678.jpg</td>
<td>140</td>
<td>140</td>
<td>4138</td>
<td>25.1818</td>
<td>Results needs more analysis since there is No Malaria</td>
</tr>
<tr>
<td>m_enos_907653432.jpg</td>
<td>140</td>
<td>140</td>
<td>4138</td>
<td>25.1818</td>
<td>Results needs more analysis since there is No Malaria</td>
</tr>
</tbody>
</table>
CONCLUSION AND RECOMMENDATION

The world of telecommunications is becoming globally powerful such that, digital media innovation becomes a factor to poverty alleviation in the developing world. To fight rampant disease outbreaks affordably, early telediagnostics and detection therefore becomes the main objective of this research project. This biomedical imaging solution has the potential to save lives in areas where health experts are limited.

While meeting the objectives above, this study has demonstrated that faster diagnosis of ailments such as malaria, skin diseases, cholera, Tuberculosis, and others is possible. We are able to monitor and trend disease progression in cancer sample specimen. With faster internet access and mobile telephony, we intend to take this study further by integrating it with a portable digital microscopy on a portable mobile application (mobile app) for automatic telediagnostics exploration in mHealth. Further, research into solar energy power for the tool to enhance its mobility, accessibility and availability needs investigations.

REFERENCES


