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The Channel-Attention U-Net: A Semantic Segmentation Mechanism for the Esophagus and Esophageal Cancer

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ABSTRACT: An image segmentation technique called Computed Tomography (CT) helps in the diagnostics and treatment of patients with esophageal disease. However, there are CT issues like the small esophagus in the scans and an irregular shape of the esophagus which complicate matters. Generalization of models don't cover all cases of esophageal cancer These are the problems that arise in dividing the esophagus and esophageal cancer into separate segments. Network extracted features have been a high research priority for some adjacent structures because esophageal carcinoma, a tumour or cancer that forms in the tissues of the lower end of the esophagus, occurs close to those organs and tissues will be presented for the very little code." What U-Net will do, according to this article, is introduce a novel channel structure — Channel-attention novel article"will provide here are The purpose of U-Net is to eliminate slices from scanning of the esophagus and esophageal cancer segmentation of the disease. This novel network distinguishes tissue layers using a Channel Attention Module (CAM) that concentrates on the features of the channels and also uses the Cross-fuse module (CFF) to expand the network's capacity for generalization. At a high levels, the higher-level features are organizational in nature, and at the lower levels, they represent less specific characteristics, like edges and contours. As a result, the network can learn a precise, accurate picture of a company, its organizational structure. In addition, 3D semi-automatically segmenting the esophagus for improved accuracy is proposed. The training set is made up of 46,400 CT images, with 11,600 images chosen at random as a validation set. Finally, 7,250 CT images were employed as the control sample set to determine how well the network was performing. Our experimental results demonstrate that the theoretical mean IoU (and standard deviation) value of our network is 0.625, while the results also demonstrate that the Hausdorff distance can be lower at 3.193.

KEYWORDS: Esophagealcancer, deeplearning, channel attention mechanism, computed tomography (CT)

I. INTRODUCTION

Many people, especially elderly people, suffer from esophageal cancer. Cancer can be detected earlier and treated more effectively by early detection and medical imaging. Using computed tomography (CT) images, radiographs are commonly used for different disorders of the esophagus since it can yield high- anatomical images.

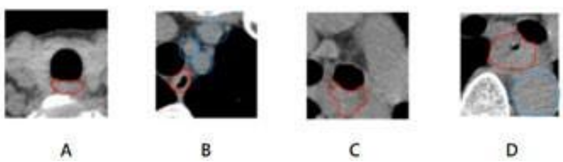

Fig1 :Esophageal (en-sahl-AY-jee) and Esophageal cancer: CT (ee-sow-fall-ay),

a slang term for esophagus, can be noted on the scans in various colour patterns: dark, light, blue, red, and almost white. The red lines are the borders between the normal esophagus and the esophagealignant, carcinogenic parts of the intestinal tract.Esophagealograms that appear blueish are the regions of the anatomy similar to the esophagus in appearance. Without air holes, A is normal; with air, it is malignant; without air, it is malignant; with air, it is deadly.

Our main results are as follows:

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The Channel Attention Module (CAM) is to adjust the CT image's tissue parameters for better matching different models. And thanks to this, the network segmentation process is made simpler. 2 The CFF model is presented. Thus, with CFFM, the network has improved the ability to identify and perceive multiple small objects of interest by pooling information from multiple levels. Thus, however, while it is on the other hand, on the other hand, on the other hand Thus, the network can gain an understanding of the shape and contour of the esophagus to help aid swallowing Due to the extremely narrow anatomy of the esophagus, the entirety of the organ cannot be assessed by a single section of a computed tomography (CT) scan. Rather, it needs to be made in conjunction with a three-dimensional representation (The diseased tissue in the 3D esophagus must be considered) Rapid segmentation and three-based reconstruction are critical therefore. Because the small percentage of the overall total CT image is esophageal and esophageal cancers, we increased the size of the 512x80 slice to 512x80 in 3D prior to rendering the overall picture. Moreover, it allows the separation of squamous cell cancer of the esophagus from the non-squamous cell types at a higher resolution. Similarly, the 2D segmentation results will be entered into the semi-automatic 3D cancer segmentation method. Using 3D esophagus segmentation, rapid segmentation is guaranteed. In the three major measures of work (work-life balance), we have established new methods that are state-of-of-the-the-art: Intersection over Union (IoU), Distribution (D) and Hdorffan (D-H) Once the 2D CT slices were segmented, the 3D model was created to re-create the esophagus and esophageal cancer. Doctors can utilise this model to verify the accuracy of the algorithm's predictions.

II.RELATED WORKS

A. U-NET AND ITS VARIANTS OF SEMANTICSEGMENTATIONTASKSINMEDICALIMAGES

Instead of back-pushing on high-level features, U-Net relies on skip connection structure. Having all of the scales integrated also empowers multiscale predictions. Medical imaging is typically uses it. To provide additional practise and learn higher levels of semantic, Alom and colleagues suggested a recurrent residual neural network (RRCNN) combination with a U-Net [Alom, et al. (1999)]. Many successes have been recorded for the R2U-Net model in vascular, respiratory, and skin data sets. U-Net networks have different uses, requiring differing amounts of depth. They concluded that, therefore, they proposed to do U-Net that varies its level of embedding and includes deep supervision in order to allow the network to select the appropriate depth [23] New Creative Uses is based on residual connections, replacing each sub-module of U-Net with a different way to use them [ResNet is the product of residual connections.] In a successful effort, Xiao et al. applied the U-Net to retinal images. not filtering the shallow features are instead passed on to the decoder, resulting in the network ignoring or emphasising other features and skewing their significance during training, causing it to produce a reduced accuracy When lower-level features are passed through a skip connection, spatial attention mechanisms are required to address issues. Although the boundary between the esophagus and the esophageal cancer may be vague, in many cases, it is a hard distinction to draw. Also, in this regard, attention models that concentrate on a specific features are not effective for the process of segmentation of the esophagus. We therefore must base our attention mechanisms on something other than U-Net.

B. ATTENTION MECHANISM IN IMAGE FEATURE ENHANCEMENT

Since the 1980s, attention modules have been used in many fields of AI, including computer vision, natural language processing, and speech recognition. Autonomous attention mechanisms such as image and natural language processing have been widely used in the treatment of images and text The spatial attention mechanism was applied in the channelization task to build a correlation between spatial features and the ch- This study was published in the Journal of Cardiovascular Interventional Techniques by Oktay et al. Our Attention U-Net has done nothing to improve the communication features. Hu and his team published SE-Net, which takes advantage of machine learning to discover which features are most important and also compresses unnecessary ones to deal with the problem of high segments in CT images, we embed a Channel Attention Module (CAM) (aka U-Net) in our channel layer that interconnects features.

C. CROSS-LEVEL FEATURE FUSION

More and more research in Semantic Segmentation has been done on neural network-based features. automate units to eliminate complex connections between the feature information in the encoder and decoder units. This feature effectively links the down-sampling and up-stages. Additionally, the symmetric encoder-decoder design is the same on both sides of the equation. technology: Hence, there are numerous medical image network elements with U-Net as the model You don't know what you've got till it's gone, [to use] According to Zhou et al., the architecture is a deeply-supervised network in which the encoder and decoder are connected through dense skip pathways, which allow the feature information captured to be distributed through various levels. was motivated by residual connection, respectively, and exchanged each submodule of the former with the latter You don't care how long you've had them, you don't care how strong, you just let it go: nine months of unemployment doesn't teach you to plan ahead for finances. Adding multiple skip connections between the encoder and decoder will increase the number of semantic

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networks and improve multi-scale segmentation. Another inspiring finding is that higher-level features combine with lower ones, as in FLE to obtain better results. Pyramidic attention network (F) uses fPN to encode low-level features before classifying or binding these low-level and high-level features together The ASPP module was developed to collect multi-scale information. The AESOP procedure allows you to efficiently produce features of different resolutions and scale by fusing them with hole-fraction convolution Information fusing effectively improves the detection effect. Cross-layer Feature Combination Modular (CLFIM) method (CFFM).

III.PROPOSED METHOD

The following procedure is described in detail in this section. The first step of the data analytics process is data pre-processing and data-augmentation, as shown in Figure 2. The robustness of the network is enhanced by data integration. Second, instruct the ChannelAtt. After training, the esophagus and esophageal morphology features can be learned, and after that, the parameters can output the predicted esophagus tumour segmentation findings Finally, the proposed semi-automatic segmentation technique loads saved and pre-segmented esophagus and segmentation methods will be combined into a 3D semi-automatic algorithm.

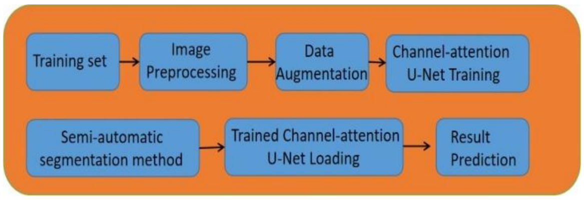

FIGURE 2.Flowchart of the proposed method for the segmentation of esophagusandesophageal cancer.
FIGURE 3. Illustration of the input data of network.

A. IMAGEPREPROCESSING

Next, we create 512 bitmap DIC images (DIC/Digital Imaging and Communications in Medicine). As is illustrated in Figure 3, the tumour size of the esophagus measures 80 millimeters on each side. This rectangle represents the CT slice to be used as an input. It is the area between the lower two sphincters, called the esophagus, that is identified and targeted by the doctor, and which is where the network sends its signals out.

B. DATA AUGMENTATION

Although in deep learning, hyper parameter tuning is critical for network robustness Esophagealacocolic and esophagealgeal cancer that appears in various positions are highlighted with the network. To boost the segmentation algorithm, we use multiple rectangles from both training and test sets to make multiple outputs. Esophageal cancer can occur anywhere in the image in the selection, especially in the middle of the selection. Due to these additions, the training set and test set are approximately five times the size of before.

C. TRAINING AND TESTING

The preprocessed esophagus and esophageal cancer images are channel supervision of the network's U-Net.
We use Adam as our network optimizer and epochs of training is defined as 30 epochs. There are four iterations in the process An essence of cross-entropy as a loss function for binary classification, but we believe this is a binary problem in which case with esophageal- anus or esophageal-cancer as the case and everything else, thus use a Binary Cross-Entropy (BX) The value that can be used for the net BCE output has a minimum constraint on its input is between 0 and 1, so we use softmax.

They have quite different structures in the esophagus, as well as in the esophageal cancer. In addition, esophageal and esophageal cancer features also differ significantly throughout the dataset. One way to describe this is to say that features that are simple are easier to recognise by the network, and features that are difficult to recognise are features that have also occurred frequently in the network. To be more correctly stated, in other words, due to large differences in features, the network will be able to fit one kind of feature quickly, but fit other kinds of features very slowly.

Creative sentence: The more data you use to train the network, the more it will over-train and the worse it will perform on novel cases. As a result of many experiments, we've raised the threshold value for loss to $ to 4. Training is initiated when the mean squared error of a batch of data meets or exceeds the threshold for a minimum value.

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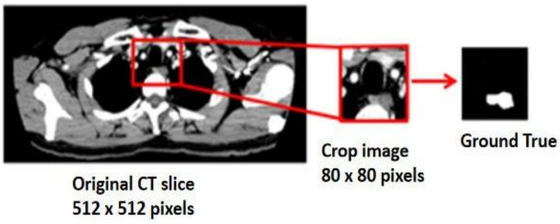

We randomly sample images from the model training set in order to the testing phase to see if the model generalisation ability holds. In contrast to a generalisation, we take a random selection of 100 items from the test set. The training sets do not contain these samples, but they have its specifications. Some state-of-of-the-the-the-the-art deep learning models are run against the models we have developed.

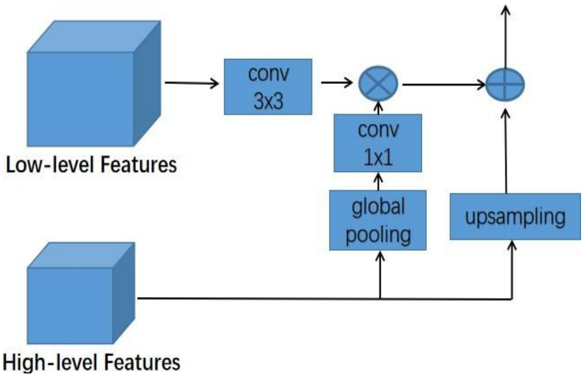

FIGURE 4. The illustration of Channel Attention Module (CAM). The high-level features guide the low-level features to emphasize or suppress related features.

1) CHANNELATTENTIONMODULE

This CAM (Channel Attention Module) is shown in Figure 4. Since the high-level semantics are abundant, this can help increase the precision of lower-level analysis. CAM will be able to measure the weight of each cable in the network Alleviating discontent in the channel "Creation, Invention, Analysis, and Modification".

$$X_{cam}=CAM(X_L,X_H) \quad (1)$$

The output of the CAM module is given by the abbreviated acronym $X\text{-}_{Cam}$. The low- and high-level feature maps were X_L and X_H, respectively.

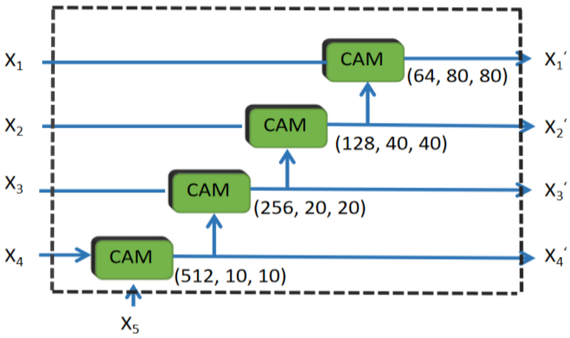

FIGURE5. Architecture of Cross-level Feature Fusion Module (CFFM) which contains four Channel Attention Module (CAM).

CAM first summarises various low-level characteristics of categories to create a context for lower-level features. These 3 convolution filters are applied to lower-level feature maps to reduce the channels of the features Unnn helps globally interprets the global features and projects them by a 1 convolution operation with batch normalisation and a ReLU activation non-function. final touches, also referred to as the 'high-end' or 'ultra-high' features, are added with the low-

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end or base features. applications that targets lower-level use of an existing application module more effectively, uses high-level features to assist with lower-level applications.

2) CROSS-LEVEL FEATURE FUSION MODULE

High level features may assist or interfere with the creation of low-oriented ones we are inspired by the pyramid of attention As more specific and granular, it promotes both detecting small objects while still providing high-level information such as borders and textures. For every encoder, we take the output feature map as the beginning point of our model. Moreover, each CAM layer acts as an input to the next layer. Thus, every CAM is used to search for channels based on various criteria. CAM is described as doing something of the following:

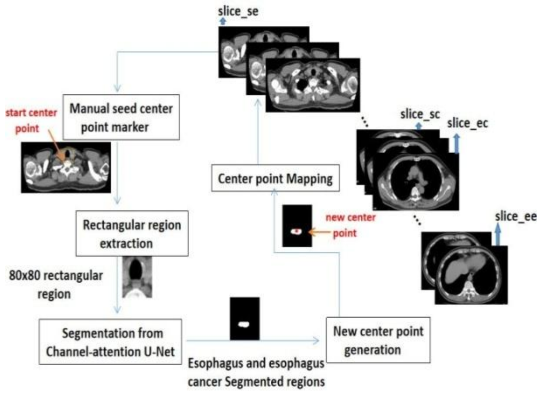

FIGURE 6. Scheme of 3D semi-automatic segmentation for esophagus and esophageal cancer: start center point is the center point of the first CT slice. slice_ce and slice_ee are the start and end CT slice of esophagus. slice_sc and slice_ee are the start and end CT slice of esophageal cancer.

IV. EXPERIMENT

I. DATASETANALYSISANDEXPERIMENTALENVIRONMENT

All medical imaging apparatus and software in the experiment are supported by the Sun Yat-sen University Imaging Center. surgery. Experienced esophageal surgeons performed CT scans on 152 people with a negative esophageal cancer diagnosis. According to the specs, here are the specifications for each CT image: Capture size field of view = 376mm × 376and field of view (or capture). The easiest way to tell is to slice into your model and count the number of teeth of the pieces of slicer and count the number of slices of your model and then multiply that by three. the region of interest on the scan was drawn and outlined by two radiologists who are highly experienced (ROI). Manually annotated using all of 13,050 CT images were collected.

We used the total of 45 sets, which consisted of both training and validation scans, to train and test on. Doctors draw the CT images of the esophagus or esophagealoma regions by hand. Total: 1,450 slices are included in the test.
Rather than using training and testing data, data mixing was used. training rectangles for the Channel Attention Network are created for each CT slice For the model we divide a proportion of 0.2 from the training set into the test set as validation. In the training set, there are 46,400 samples. Eleven thousand and seven hundred is almost exactly one six thousand more than the total number of samples in the validation set and 5,250 less than the total number of samples in the test set.

The training set contains various esophageal- gast and esophageal tumours in FIGURE 8. Esophageal and esophageal cancer, as well as esophageal carcinoma, cannot be determined solely by location nor by the shape of some definite tissue groupings, creating a huge problem for the doctor.

The following test environment: Ubuntu 16.04, python 3.6, and a GTX 1080Ti were used:

II. EVALUATION METRIC

These three pixel-level measurements are compared with other approaches to the use of Intersection Over Union (IoU), Dice (D) and Louvain Distance (HD) and assessed using their comparative accuracy: Intersection over Union (IoU), Dice (D) and Hausdorff Distance.

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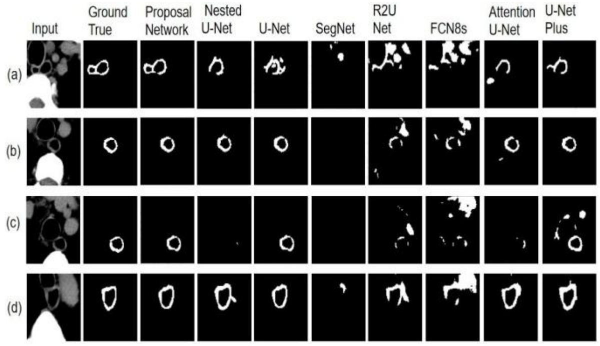

FIGURE 7. Comparison of esophagus segmentation results between the proposed model and seven other deep learning models

$$\mathrm{IoU} = \frac{\mathrm{TP}}{\mathrm{FN} + \mathrm{FP} + \mathrm{TP}}$$

The amount of overlap between the target area and the suggested network is the true positives; that is, the areas where the doctors manually marked target and suggested overlap. The FN represents false negative, which means there was no oral cancer detected. False positives mean the network proposal classified the area as the esophagus as having this cancer. Intersection and union of two sets is what IO signifies. The 'i.o.o.u' score measures image segmentation performance at the pixel level. The possible values of IoU can range from zero to one. as the inter-column spacing, the greater the overlap between the two regions, and the smaller the intercolumn voltage.

III. RESULTS AND ANALYSIS

To better seg-mentation, we used the existing 6 state-of-of-the-the-the-art models, R2U-Net, Attention, and FCN, which is shown in FIGURE 9 and 10. There are seven comparative models used in the encoder and decoder structures, all of which being almost identical, only U-Net surpasses non-U-Net with increased precision. The reason for the effect is that U-Net, and others, use the concatenation instead of integration with the skip connection and up-sampling feature maps in the decoder. Whenever you add something to the data, its ability to retain information suffers. To put it another way, the encoder and decoder of R2U-Net are built from multiple recurrent convolutionalations. This has aggravated the problems with R2U because of how it's been over-fitting our dataset. Whereas the network is fast at deviating a part of the esophagus into an air hole, network U and our esophagealectomy treatments diverge on that point. Additionally, the software has difficulty finding small gastric air gaps when segmenting the esophagus.

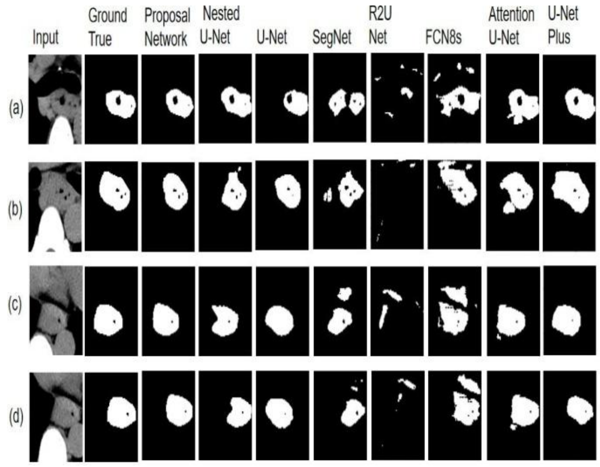

FIGURE8.Comparison of esophagealcancer segmentation results between the proposed model and seven other deeplearning models.

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TABLE 1.Comparison between traditional image processing method for esophagussegmentation and the proposed method.

Methods \ Measures	IoU	DV	HD (mm)
Markov chain model [3]	0.548	0.652	3.587
Atlas selection [4]	0.537	0.640	7.301
Skeleton-shaped model [5]	0.580	0.682	7.785
Channel-attention U-Net	**0.625**	**0.739**	**3.177**

U-Net works to extract all the information from the highest levels. The former focuses on using multiple features and layers and trains spatial attention along the way, the latter involves processing several features sequentially. Neither of them can blend lower level features with upper level features or guide the selection of low-level features with upper-level features are all that well-suited for each other, though Our cable system uses channel attenuation

The main difference between a feature module and a layer is that a module (CAM) fuses specific features, but also utilises a cross- CFF module (CAM) to determine which low-level features are related to the shape and boundary of the esophagus on the basis of higher-level features, using spatial features like texture and shape. Additionally, the segmentation effect and generalisation of this phenomenon is covered.

V.CONCLUSION

Not only is it the process of breaking down and recovering of the physical structure of the egg useful, but also the production of quality semen that aids in both diagnosing and treating the egg cancer. It has been shown in this paper that we have developed a deep network, named Channel-attention U-Net, which retains only the relevant channel information and incorporates low-level information on channels at the lower levels. Features are de-cleaned by means of the Chan-el Attention Module (CAM), with the un-important ones removed on the other hand, the network highlights important characteristics. With this technique, the network has a better chance of learning the morphological features of the esophagus and/esophageal shape simultaneously. Furthermore, we have arrived at the conclusion that models using U-Net will have greater capacity for generalisation than those with non-U architecture When the Attention network was applied, its spatial attention mechanism was found to be inferior to the U-Net; this suggested that network effects would not be improved even if the spatial attention mechanism was not included. Other than the seven other models, our prediction method has an advantage over the three IOU, DV, and HD indicators. In a semi-automatic segmentation system, the trained network will be used to separate 3D esophagus and esophageal cancer. Once the segmentation has been applied, the doctor will be able to look inside the patient's body using a computed tomography (CT) scan to help with diagnosis.
We had to go through many segmentsation tests to find out that the separation network on thin networks was lacking. if there is a very little difference between one tissue and another, a number of other tissues will sometimes be seen as follow-on. If there is air between the esophagus and the food pipe, the network will be totally unaware of it. We'll fix this issue in the future by implementing a creative solution.

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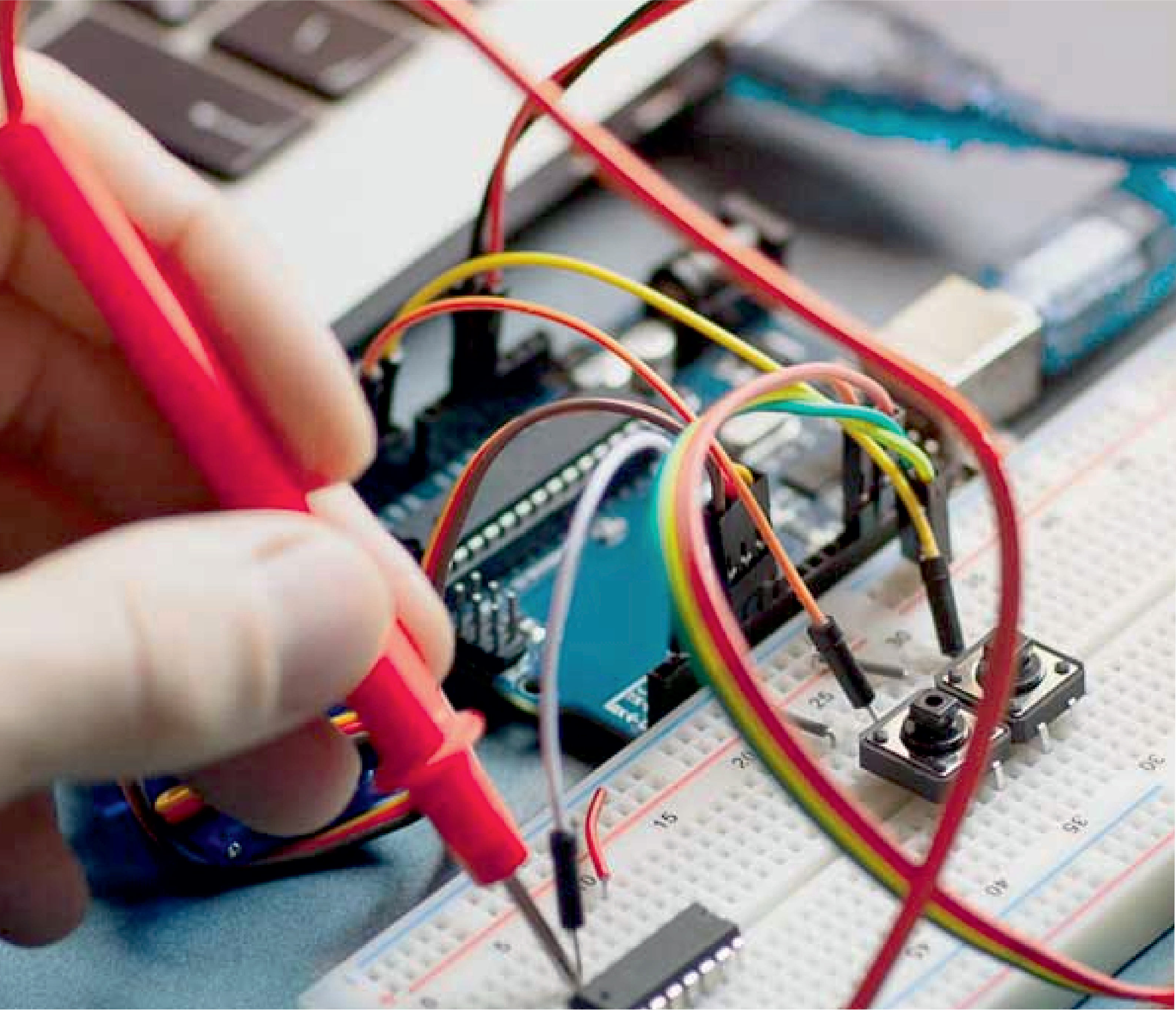

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