The Application of Mobile Devices for the Recognition of Malignant Melanoma

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Abstract: Robotic systems and autonomous decision making systems are increasingly becoming a significant part of our everyday routines. Object recognition is an area of computer science in which automated algorithms work behind a graphical user interface or similar vehicle for interaction with users or some other feature of the external world. From a user perspective this interaction with the underlying algorithm may not be immediately apparent. This paper presents an outline of a particular form of image interpretation via mobile devices as a method of skin cancer screening. The use of mobile hardware resources is intrinsically interconnected with the decision making engine built into the processing system. The challenging fundamental problem of computational geometry is in offering a software - hardware solution for image recognition in a complex environment where not all aspects of that environment can fully be captured for use within the algorithm. The unique combination of hardware - software interaction described in this paper brings image processing within such an environment to the point where accurate and stable operation is possible, offering a higher level of flexibility and automation. The Fuzzy logic classification method makes use of a set of features which include fractal parameters derived from generally understood Fractal Theory. The automated learning system is helping to develop the system into one capable of near-autonomous operation. The methods discussed potentially have a wide range of applications in 'machine vision'. However, in this publication, we focus on the development and implementation of a skin cancer screening system that can be used by non-experts so that in cases where cancer is suspected a patient can immediately be referred to an appropriate specialist.

1 INTRODUCTION

The wide-scale availability of mobile devices offers the public a range of hardware with built in digital cameras, with an associated increased potential for digital image processing. The fast-growing image capturing CCD/CMOS array development is capable of generating ever larger amounts of data for processing. The newer internet connections for such devices, with 3G and 4G data transfer rates, could deliver an image to power an image processing station in an appectable period of time. Storage facilities have also developed to extremely large capacities, to the extent that a human is unable to process these volumes of data by manual/visual methods. Given this situation, technological developments in industry and science will, in future, have to rely increasingly on stable and robust robotic tools to interpret the acquired data. This applies significantly to the area medical diagnostics, although the application of automated approaches in this field still presents a number of challenges. Innovations in the application of automatic image recognition will increasing help meet these challenges in the future.

The increased storage capacity, improved data transfer rates and processing speeds now enable the development of image recognition tools for small hand-held devices. A mobile device's camera and navigational human interface leads to a relationship between the software and hardware built into the device; there is then a further relationship with the image processing server that assists in the processing of the complex mathematical equations that necessarily underpin computerised image processing.

The particular concern of this paper is the use of such devices for the recognition of malignant

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melanoma associated with abnormal moles. A key challenge is to overcome the limited ability of computerised image processing techniques to replicate the visual techniques that a human specialist uses when making similar assessments. Consequently, the processes used by computerised image recognition models have to be capable of producing a level of accuracy of assessment and diagnosis that is comparable to that achieved by specialists, but at the same time this must be done using approaches and algorithms that are fundamentally different from the process of human interpretation. A key factor is the need for segmentation, that is the process of dividing a given image into a number of segments that will each have something to contribute towards carrying out an analysis in a meaningful way. A initial task is to determine the boundaries of the captured image so that the analysis is only applied where appropriate. The ability to compensate for variations in features, light conditions and the nature of image itself requires an altogether more complex approach.

These challenges can be addressed in a number of ways. For example, the consideration of colours and patterns within the image recognition algorithm contribute towards the definition of boundaries and segments, including the essential external boundary of the image. Much of this process is concerned with the identification of edges of one sort or another (Abdou and W.K.Pratt, 1979). Indeed this identification is a pre-requisite for image recognition and a fundamental step towards ensuring stability and robustness in decision-making. Establishing the relevant segments of the image depends on two essential features of the image: firstly, those areas that can be considered similar to each other; and secondly, the identification of discontinuity. The task of the image recognition process is precisely to make the distinction between those features.

The algorithm used in this application includes a number of innovations. It does not depend on the identification of first and second order gradients in a conventional manner, nor does it make use of thresholds in order to consider binarisation. Rather, self-organising fuzzy sets are utilised in order to optimise the Knowledge Data Base (KDB) for the application. The system includes features that are based on the textural properties of an image defined in terms of fractal geometric parameters including the Fractal Dimension (FD) and Local Texture Detectors(LTD) which is an important theme in medical image analysis. However, in this paper we focus on one particular application, namely, the skin cancer diagnosis for screening patients through a mobile device.

2 SKIN CANCER FEATURE DETECTION AND CLASSIFICATION

Colour image processing is becoming increasingly important in object analysis and pattern recognition. There are a number of algorithms for understanding two- and three-dimensional objects in a digital image. The colour content of an image is very important for reliable automatic segmentation, object detection, recognition, classification and contributes significantly to image processing operations required and the object recognition methodologies applied (Freeman, 1988). Colour processing and colour interpretation is critical to the diagnosis of many medical conditions and the interpretation of the information content of an image by both man and machine. (e.g. (E.R.Davies, 1997), (Louis and Galbiati, 1990) and (Snyder and Qi, 2004)).

A typical colour image consists of mixed RGB signals. A grey-tone image appears as a normal black and white photograph. However, on closer inspection it may be seen that it is composed of individual picture cells or pixels. In fact, a digital image is an [x, y] array of pixels. We may already have a given image of an object that can be described by the function $f(x,y)$ and has a set of features $S = \{s_1, s_2, ..., s_n\}$. The key task is to examine a sample and to establish how ‘close’ this sample is to the reference image, requiring the creation of a function that can establish the degree of proximity. All recognition is a process of comparing features against some pre-established template, a process that has to operate within the bounds of certain conditions and tolerances. We may consider four stages in this process: (i) image acquisition and filtering (in order to remove noise, although even at this stage, a proper understanding of what noise is and what may be pertinent information is essential); (ii) accurate location of the object, through edge detection (iii) measurement of the parameters of the object; and (iv) an estimation of the class of the object. Various aspects of these stages are considered below, with a focus on those features of design and implementation that are most advantageous for the development of applications for skin cancer screening.

The image to be acquired has to be suitable for integration within the application. In the case of mobile devices the camera is intrinsically bound up with the operating system of the device. Images obtained using a typical camera of this type are relatively noise free and are digitised using the mobile device’s standard CCD/CMOS camera. Nevertheless, the capturing of good quality images with consistent brightness and contrast features remains critical. The most important aspect is compatibility with the sample images used. The system discussed in this paper is based on an object detection technique that includes a novel mobile device segmentation method that must be applied at the time of taking the picture. This includes those features associated with an object for which fractal models are well suited (Dubovitskiy and Blackledge, 2012), (Dubovitskiy and Blackledge, 2008), (Dubovitskiy and Blackledge, 2009). This system provides an output (i.e. a decision) using a knowledge database which generates a result - the diagnoses. The new 'expert data' in the application field creates a knowledge database by using an automated self learning technique. The old supervised training model for objects is well known (Zadeh, 1975).

The recognition process is illustrated in Figure 1, a process that includes the following steps:

1. Image Acquisition and Filtering.
   A mobile device capture of a physical object is digitally imaged and the data transferred to memory, e.g. using current image acquisition hardware available on a mobile device. The image is filtered to reduce noise and to remove unnecessary features such as light flecks. The most important of these is the Preliminary image Guideline Function(PGF). The PGF works recursively to reach a stable object fixation. As soon as an object or mole in our application is detected the system transmits it to the server.

2. Special Transform: Edge Detection.
   The digital image function $f_{m,n}$ is transformed into $\tilde{f}_{m,n}$ to identify regions of interest and provide an input dataset for segmentation and feature detection operations (Nalwa and Binford, 1986). This transformation avoids the use of conventional edge detection filters which have proved to be highly unreliable in the application under consideration here.

3. Segmentation.
   The image $\{f_{m,n}\}$ is segmented into individual objects $\{f^1_{m,n}\}, \{f^2_{m,n}\}, \ldots$ to perform a separate analysis of each region. This step includes such operations as auto thresholding, morphological analysis, edge or contour tracing (Dubovitskiy and Blackledge, 2009) and the convex hull method (Dubovitskiy and McBride, 2013).

4. Feature Detection.
   Feature vectors $\{x^1_k\}, \{x^2_k\}, \ldots$ are computed from the object images $\{f^1_{m,n}\}, \{f^2_{m,n}\}, \ldots$ and corresponding transformed images $\{\tilde{f}^1_{m,n}\}, \{\tilde{f}^2_{m,n}\}, \ldots$. The features are numeric parameters that characterise the object, including its texture. The computed vectors consist of Euclidean and fractal geometric parameters together with one and two dimensional statistical measures. The border of the object is described in one-dimensional terms while the surface on and around the object is delineated in two dimensions.

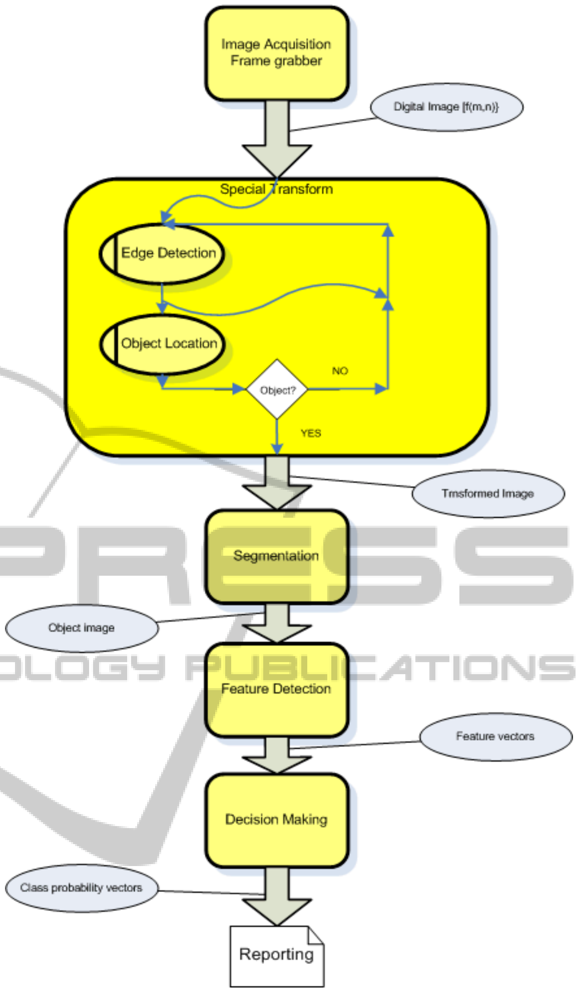

Figure 1: Recognition process.

5. Decision Making.
   This involves assigning a probability to a predefined set of classes (Vadiee, 1993). Class probability vectors are estimated through the application of fuzzy logic (Mamdani, 1976) and probability theory to the object feature vectors $\{x^1_k\}, \{x^2_k\}, \ldots$. Establishing a quantitative relationship between features and class probabilities is a critical aspect of this process, and one that has previously caused problems, i.e.

$$\{p_j\} \leftrightarrow \{x_k\}$$

$\leftrightarrow$ indicates a transformation from class probability to feature vector space. A 'decision' is the estimated class of the object coupled with a probabilistic determination of accuracy (Sanchez, 1976).

Associations between the features and object pattern attributes forms an automatic learning context for the KDB (Dubovitskiy and Blackledge, 2009),(Dubovitskiy and Blackledge, 2008), whereby the representation of the object is assembled into the feature vector (Grimson, 1990), (Ripley, 1996). The KDB depends on establishing equivalence relations that express a fit of evaluated objects to a class with independent semantic units. The pattern recognition task is accomplished by assigning a particular class to an object. In the next section we consider the main focus of this paper, the use of mobile devices, and the loop back to the automated learning algorithm.

2.1 Mobile Device Picture Acquisition

The graphical user interface of mobile device provides PGF. The user has to be taken through an automated system to evaluate light condition, focus, shadow and other relevant features. If some of the conditions are not suitable for image recognition the system provides guidelines to assist with the process. The guidelines may even ask the user to go to another location where the light will be sufficient to support the decision making process. The screen message will indicate that the "best result could be achieved at that point". The use of the inbuilt compass and gravitational sensors of mobile devices helps to produce exceptionally good recognition results. The gravitational sensor in combination with the object's position can guide the user to capture the most suitable image perspective. The compass assists to select the best lighting condition to avoid the point of evaporation and shadows.

The block scheme diagram for the mobile device segmentation for the mole and skin location is present in Figure 2 and includes the following steps:

The Figure 2 represents a mobile device section of the Malignant Melanoma recognition process. The mobile device component has a loopback via PGF and it would not accept an image with low quality, itself applying a quality control system to the initial stages of the process of skin cancer recognition. The main steps of the mobile system are present in four sections of figure 2. The object acquisition is shown in section 1 2 and it is a standard mobile device camera control module. The output of section 1 is an image function $f(x,y)$ with set of exposure parameters $E = \{e_1, e_2, ..., e_n\}$. Mobile device pre-processing software is present in section 2 and has set of parameters the value between 0....1. The set of mobile device

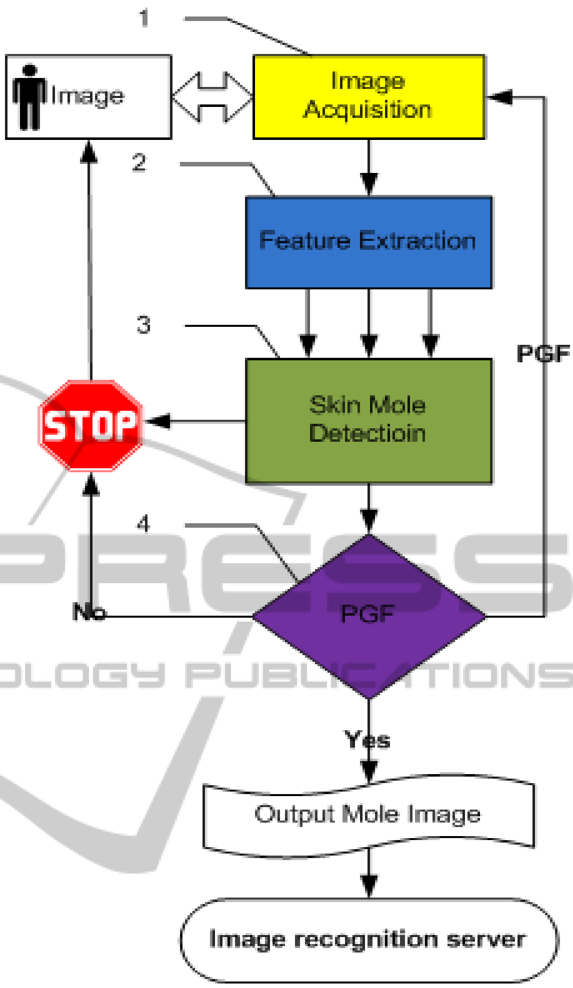

Figure 2: Mobile device mole - skin searching process.

features is $P = \{p_1, p_2, ..., p_n\}$. Each parameter represents the current environment for image capture, for example Exposure time, Aperture, Focus section by X and by Y, Light uniformity by X and by Y, Skin distribution, Mole positions, Mole distribution. Then the vector $P = \{p_1, p_2, ..., p_n\}$ is input to section 3. Section 3 is responsible for making decisions about the image environment. The decision making function is:

$$S(d_{exposure}) = \frac{2\pi(P_{n+1} - P_n)}{D_{n+1} - D_n}$$

The output S is the representation of the environment condition. If S is closer to 0 then the user is advised to point to the mole. Then if S is closer to 1 the the system routes via PGF. The actual value of S is device dependent and could be set through the software installation procedure. The D is the scalar distance for each parameter P for the particular number of iteration n. Section 4 provides guidelines for the user. The PGF is the probabilistic function with a vector of values of parameters $\mathbf{S} = \{d_i\}$. The PGF transform the vector of values of parameters $\mathbf{S} = \{d_i\}$ by use of the membership function $m_j(x)$ from Fuzzy Logic theory and the output is vector $\mathbf{G}$ by using the following expression:

$$\mathbf{G}_{i,j} = \left| 1 - \sum_{k=1}^{N} \left(p_{i,j}(\mathbf{S}_{i,j}^{k}) - \langle p_{i,j}(\mathbf{S}_{i,j}) \rangle \right) p_{i,j}(x_{i,j}^{k}) \right|.$$

The matrix of weight factors $p_{i,j}$ is formed at the stage of software installation to the mobile device accordingly. In other terms, it is touch pad calibration, assigning weight coefficients for the i^{th} parameter and j^{th} class.

The result of the weight matching procedure is that all parameters $\mathbf{G}_{i,j}$ have been computed. Then each $\mathbf{G}_{i,j}$ has a semantic table of guide rules for the touch pad and user. After several iterations the PGF's parameters $\mathbf{G}_{i,j}$ is to come to the 1. At that point the image looks as shown on Figure 4 and ready to be transferred to the main decision making server.

The novel PGF procedure allows the saving of a lot of computational resources at the usual image pre-processing stage for an accurate decision making function. The usual low brightness, contrast, image graininess and geometrical distortions no longer inhibit the most efficient edge detection and texture computation.

2.2 Fuzzy Logic Automated Leaning

Object recognition is another difficult part of digital image processing. Each object has to be present in computer memory with all possible characteristic features and as compact as possible, in order to allow real time processing. The basis for the object's area is textural feature. The Fractal structure is most suitable for describing such objects from the natural world. Some Euclidean and morphological measures are also captured as part of property of the object. All objects have a list of parameters. This list of parameters has been considered in previous publications (Dubovitskiy and Blackledge, 2012), (Dubovitskiy and Blackledge, 2008), (Dubovitskiy and Blackledge, 2009) and can be varied depending on the application. Using an excessive number of parameters does not impact the accuracy of recognition but can slow down the whole process. Here we present a novel approach to the organising of membership function through a special automated learning procedure. The use of a Fuzzy Logic engine with automated membership function formation has several advantages. The one disadvantage is that we have to extend the set of parameters for an object with extra characteristic values. But as computational resources in modern CPU and FPGA are nearly unlimited this is not a problem and as a result we obtain a user friendly system. The excessive features which do not characterise an object will be insignificant by putting their coefficient to 0 in the membership function during learning time. The whole process can be divided onto three stages: Decision making, Learning and Correction process.

The Fuzzy Logic membership function is present in Figure 3:

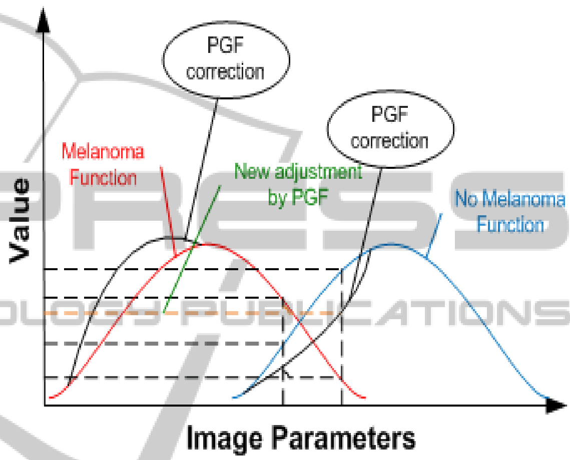

Figure 3: Fuzzy logic automated leaning.

The information about the object's classes is stored in the KDB and can be stored as a file (*.kdb) and loaded to the system depending on the application. The object information in the KDB is represented through probability coefficients for the particular class. The class probability is vector $\mathbf{p} = \{p_j\}$. It is estimated from the object feature vector $\mathbf{x} = \{x_i\}$ and membership functions $m_j(\mathbf{x})$ defined in the knowledge database and is shown on the blue and green lines on Figure 3. If $m_j(\mathbf{x})$ is a membership function, then the probability for each j^{th} class and i^{th} feature is given by value vector:

$$p_j(\mathbf{x}_i) = \max \left[\frac{\sigma_j}{|\mathbf{x}_i - \mathbf{x}_{j,i}|} \cdot m_j(\mathbf{x}_{j,i}) \right]$$

where σ_j is the distribution density of values $\mathbf{x}_j$ at the point $\mathbf{x}_i$ of the membership function. The next step is to compute the mean class probability given by

$$\langle p \rangle = \frac{1}{j} \sum_j \mathbf{w}_j p_j$$

where $\mathbf{w}_j$ is the weight coefficient matrix. This value is used to select the class associated with

$$p(j) = \min \left[(p_j \cdot \mathbf{w}_j - \langle p \rangle) \geq 0 \right]$$

providing a result for a decision associated with the j^{th} class. The weight coefficient matrix is adjusted during the learning stage of the algorithm.

The automatic learning procedure uses the PGF settings from the mobile device. These settings provide information about image quality. The $\mathbf{G}_{i,j}$ vector is used to consider the correction value at each recognition process. The correction value coefficient is stored separately and updates the main KDB once a day. The presence of correction value is not guaranteed to be used for membership function formation. The decision to use automated correction is defined by assessing the density distribution for the membership function for each class of objects. The use of density propagation as part of a particular class function is present in Section 2.3 and we use low density as the indicator for correction. The actual value is mobile device hardware dependent.

2.3 Image Recognition Server

The result of the image recognition process is presented via the GUI interface for the image processing server on Figure 4. The device returns the diagnosis and graphical comments to the user. The system can provide further recommendations, depending on country of application, including contacts of a local GP or other health care provider as necessary.

The decision criterion method considered here represents a weighing-density minimax expression. The estimation of decision accuracy is achieved by using the density function

$$d_i = |\mathbf{x}_{\sigma_{\max}} - \mathbf{x}_i|^3 + [\sigma_{\max}(\mathbf{x}_{\sigma_{\max}}) - p_j(\mathbf{x}_i)]^3$$

with an accuracy determined by

$$P = \mathbf{x}_j p_j - \mathbf{x}_j p_j \frac{2}{\pi} \sum_{i=1}^{N} d_i.$$

The system has been tested on 654 available images of skin conditions and produced an overall accuracy of approximately 74 percent correct responses. The correct response is when the recognition system is assigning the same class and precision within 10 percent deviation from the result of a dermatologist or human eye estimate. The comparison to the biopsy is not producing better performance as the robot is the copy of dermatologist. There are some cases when even a dermatologist would be unable to make a certain decision without special equipment. The operational use of the automated correction function the system can deliver the highest accuracy. The best result would be achieved if we could get agreement for the estimate class separation for precision between

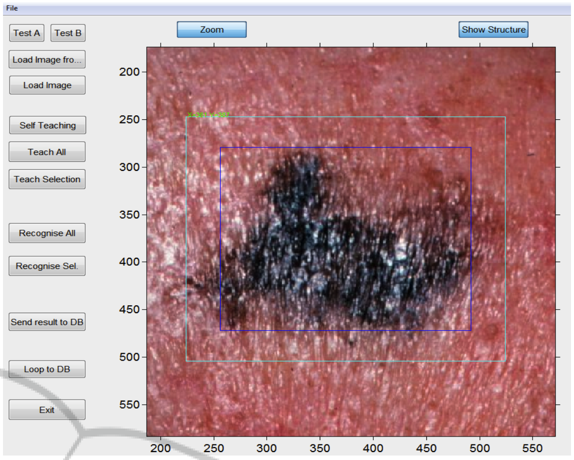

Figure 4: Image recognition server.

several dermatologists for initial setup. However, due to ethical confidentiality we are unable to publish testing data due to nondisclosure agreements. In difficult cases an expert could interact with the image recognition robot to adjust the settings for a particular mobile device.

In practice it is difficult to get exactly the same skin evaluation parameters from several doctors. The problem is with precision - how certain are they with the diagnosis. By mixing knowledge databases of different sources we create chaos in automated decision making. In our current paper we have decided to evaluate the system with one doctor for now.

3 CONCLUSIONS

The focus of this paper is Malignant Melanoma screening and in particular with the process of developing a methodology for implementing applications for such screening via mobile devices. The approach we have described involves two essential elements: (i) the partial analysis of an image in terms of its fractal structure on a mobile device CPU to get the best exposure condition for the available camera (ii) an automated learning system via a fuzzy logic engine to classify an object based on its euclidean and fractal geometric properties, achieved via access to the image processing server. The combination of these two aspects is used to define an approach to image processing and an image analysis engine that is unique. The inclusion of mobile device parameters - in terms of improving vision systems such as the one considered here - remains to be fully understood and will form part of future investigations.

As things currently stand, the approach to the analysis of images described above is not in itself sufficient as a system of image recognition and classification. However, increases in processing rates, the growth of the availability of relatively cheap digital storage and the capacity to transfer data to and from an image processing server at high speed all contribute towards a significant future potential for the use of hand held devices in the diagnosis of skin cancer associated with moles. Future work will include improvements to the automation of the fuzzy logic engine used with current hardware and mobile devices. As reliability and validation is extended there is considerable potential for the expansion of the approach we have described within the context of medical screening and to other areas of application beyond the medical sphere.

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