

A SYSTEM AND METHOD FOR ORTHOPAEDIC PROSTHESIS DESIGN

TECHNICAL FIELD

5 The present invention relates to a system and method for orthopaedic prosthesis design.

BACKGROUND

10 Lower limb bone defects present a considerable and complex challenge in orthopaedic medicine, especially when the bone defects affect critical weight-bearing structures of a patient (i.e., human) such as the femur, tibia, and fibula. These defects can arise from various etiological factors such as for example trauma, neoplastic conditions, congenital abnormalities, open fractures, infections, and failed arthroplasty procedures. These
15 bone defects can require sophisticated treatment approaches due to their impact on patient mobility and quality of life.

One treatment approach involves the use of 3D-printed prostheses, which offers personalized solutions for patients with bone defects. However, this process involves
20 several time-intensive steps that significantly impact the treatment timeline. The first major time-consuming phase is medical image segmentation, where CT scans must be carefully processed to create accurate three-dimensional representations of the patient's anatomy. This segmentation process, which can take several hours to days depending on the complexity of the defect and the quality of the imaging data. This
25 segmentation i.e., 3D modelling process requires skilled professionals to manually or semi-automatically separate bone structures from surrounding tissues and identify the precise boundaries of the defect.

Following segmentation, the design phase of the prosthesis presents another
30 challenging phase. The design phase requires significant time investment and expert engineers and medical professionals to create such prostheses. Engineers and medical professionals must collaborate to create an orthopaedic prosthesis design that not only fits the anatomical defect perfectly but also meets biomechanical requirements for weight-bearing and functionality. The design phase typically requires several days to
35 weeks, as each iteration must undergo careful review and potential modification to ensure the final prosthesis will provide optimal functional outcomes while minimizing the risk of complications. This meticulous attention to detail, while time-consuming, is crucial for ensuring the long-term success of the orthopaedic prosthesis.

40 SUMMARY OF THE INVENTION

It is desirable to provide a system and/or method for orthopaedic prosthesis design and construction that can be used to create an orthopaedic prosthesis quicker than
45 commonly used methods.

The present invention relates to a system and method for orthopaedic prosthesis design and construction. In particular, the present invention relates a system and method for automated orthopaedic prosthesis design and construction that provides a patient specific i.e., a custom prosthesis. The prosthesis may be an implant that may be implanted into a patient.

In one example the present invention may also relate to a system and method for generating a three-dimensional (3D) model of a patient's bone based on one or more two dimensional (2D) medical images.

According to a first aspect, the present invention provides a computer-implemented method for automated orthopaedic prosthesis design, comprising:

- receiving at least one medical image of a bone of a patient,
- generating a three-dimensional (3D) model of the bone from the at least one medical image,
- identifying a region of the bone with a bone defect,
- generating a defect reconstruction model,
- generating a 3D prosthesis model (i.e., 3D implant model) that corresponds to the defect reconstruction model, wherein the 3D prosthesis model is patient specific.

The method is advantageous because it provides an automated method to segment medical images of a bone of a patient and automatically generate a customised prosthesis to correct a bone defect. The method provides a faster and more efficient method of segmenting medical images as compared to the manual segmentation method utilised. The method is also advantageous because it results in a 3D prosthesis model that fits better with a patient anatomy as compared to the current manual prosthesis fabrication methods.

The 3D prosthesis model corresponds to an orthopaedic prosthesis that can be placed in a patient e.g., on a patient's bone to correct a bone defect.

In one example the method comprises the additional step of exporting the 3D prosthesis model for 3D printing an orthopaedic prosthesis that corresponds in shape and configuration to the 3D prosthesis model based.

In one example the reconstruction model is a 3D model of a portion of a bone that corresponds to a normal bone without the bone defect.

In one example the reconstruction model is indicative of a prosthesis that can be attached to the bone in the region. The reconstruction model may be similar in shape, size and configuration as a prosthesis (i.e., an implant) that can be attached to the patient's bone.

Optionally, the orthopaedic prosthesis may be an implant that is implanted into a patient. The implant i.e., orthopaedic prosthesis may be surgically attached to a bone of a

patient once the bone defect is surgically removed. The implant i.e., prosthesis can allow the surgically modified bone to heal and function as normal once the prosthesis that is generated by the method described herein is surgically attached to the bone i.e., implanted into the patient.

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In one example, the reconstruction model may be presented on a user interface on the 3D bone model thereby illustrating how a corrected bone should look.

10 In one example the method comprises receiving multiple medical images. In one example, each of the medical images may comprise CT scans of a bone or X-rays of a bone or other medical images.

In one example the method comprising the additional steps of:

15 performing volumetric segmentation of the medical image,
generating the 3D model of the bone based on the volumetric segmentation.

In one example the step of performing volumetric segmentation comprises the additional steps of:

20 pre-processing the received at least one medical image by normalization and/or standardization,
extracting contextual information from the at least one medical image,
reconstructing spatial details via up-sampling,
generating the 3D model of the bone based on the contextual information and the reconstructed spatial details.

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The method is advantageous because it provides an improved and automated method for segmenting new patient medical images. The automated segmenting method is quicker than a manual method that is currently used.

30 In one example the step of extracting contextual information comprises the steps of:

performing 3D convolutions on the at least one medical image,
performing batch normalization on the at least one image and/or the 3D convolutions, and;
performing ReLU activation.

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In one example, the method comprising the additional step of determining a surgical pathway to remove the bone defect and presenting the determined surgical pathway on a user interface.

40 In one example the step of determining a surgical pathway comprises the additional steps of:

identifying a cut to remove the bone defect, wherein identifying the cut includes determining the size and shape of a cut to remove the bone defect,
presenting the identified cut on a user interface,
45 determining a position for the reconstruction model to correct the bone defect,

determining a fixation arrangement to position and attach an prosthesis (i.e., an implant) on the bone to correct the bone defect.

5 In one example the 3D prosthesis model is generated based on the identified cut, reconstruction model and the fixation arrangement.

In one example the 3D prosthesis model is customized in shape and configuration to match the patient's bone, such that the 3D prosthesis model is patient specific.

10 In one example the method steps are performed by a 3D U-net model comprising an encoder path, a decoder path and skip connections linking corresponding encoder and decoder layers, wherein the encoder path is adapted to capture contextual information and the decoder path adapted to reconstruct spatial information.

15 In one example the method comprises the step of 3D printing an prosthesis based on the exported 3D prosthesis model. The 3D prosthesis model may be exported in an appropriate format to be processed and printed by a 3D printer. The 3D printed prosthesis may be printed from a biocompatible material.

20 The method is advantageous because it enables production of custom prosthesis (i.e., orthopaedic implant) that fits better with a patient's anatomy, resulting in reduced surgery times, improved prosthesis fit and better post operative results.

25 According to a second aspect, the present invention provides a machine learning model for automated orthopaedic prosthesis design and construction, in particular for use in the method of any one or more of the statements above, comprising:

an encoder path configured to capture contextual information,
a decoder path adapted to reconstruct spatial information, and;
skip connections linking corresponding encoder and decoder layers.

30 The machine learning model is advantageous because it automatically processes medical images and generates a custom prosthesis model that can be printed. This provides time savings on image segmentation, provides a more accurate prosthesis model and can improve cost effectiveness and result in faster creation of prostheses (i.e., implants).

35 In one example of the machine learning model the encoder path comprising a plurality of layers, and the decoder path comprising a plurality of layers, and the machine learning model is a 3D U-net model.

40 In one example of the machine learning model the encoder path comprises a plurality of 3D convolution layers, each layer is followed by or includes batch normalization and ReLU activation. Optionally, the encoder path may include average pooling after each convolution layer.

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In one example the encoder path is a contracting path, and the decoder path is an expanding path. In one example the skip connections link corresponding encoder and decoder paths. In one example, skip connections assist with backward flow of data.

5 In one example the input data may comprise 3D CT scans. The 3D CT scans may be pre-processed prior to feeding into the 3D U-net model by normalisation and standardisation.

10 In one example the encoder path is configured to extract contextual information using 3D convolutions, batch normalisation and ReLU activation.

According to a further aspect, the present invention provides a data processing apparatus for automated orthopaedic prosthesis design comprising means for carrying out the method of any one or more of the method statements above.

15 In one example the data processing apparatus may be configured to execute the machine learning model described according to any one or more of the statements above.

20 In one example the data processing apparatus may be configured to execute a 3D U-net model that is trained to process input medical images and is capable of accurately segmenting new patient medical images for optimised orthopaedic prosthesis design.

25 According to a further aspect, the present invention provides a computer program comprising instructions which, when the program is executed by a computer, cause the computer to carry out the method of any one of the method statements above.

30 According to a further aspect, the present invention provides a computer-readable medium comprising instructions which, when executed by a computer, cause the computer to carry out the method as per any one or more of the method statements above.

35 According to a further aspect, the present invention provides a computer-implemented method of training a machine-learning model for automated orthopaedic prosthesis design, in particular the machine-learning model described herein, comprising:

receiving an input training dataset comprising a plurality of medical images with a bone with a bone defect and ground truth segmentations;

feeding the input training dataset through convolution layers of the 3D U-net model,

40 optimising model parameters using combination of Dice coefficient loss and binary cross entropy,

enhancing generalisation by applying one or more variability techniques, and;

monitoring performance of the model based on a validation dataset to ensure convergence and reduce overfitting.

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In one example, during training the encoder path uses 3D convolutions, batch normalisation and ReLU activation. The decoder path during training performs up-sampling operations and utilises skip connections for detail preservation.

- 5 In one example a training dataset for use in the method of training a machine-learning model as described herein, comprising:
- input data, wherein the input data comprises a plurality of images or models with one or more bone defects,
 - output data, wherein the output data comprises a plurality of images or models
- 10 of normal bones.

In one example, the input data may include 2D images, 3D bone reconstructions i.e., 3D bone models, 3D bone models with bone defects. The bone defects may be manually created by removing bone section to simulate bone defects.

- 15 According to a further aspect, the present invention provides a system for automated orthopaedic prosthesis design comprising:

- a computing apparatus comprising a processor and a memory unit, the processor and memory unit being operatively coupled to each other,
- 20 the memory unit adapted to store instructions which, when executed by the processor cause the computing apparatus to perform a method for automated orthopaedic prosthesis design described herein.

- 25 According to a further aspect, the present invention provides a system for automated orthopaedic prosthesis design comprising:

- a segmentation module, the segmentation module configured to:
 - receive at least one medical image of a bone of a patient,
 - generate a three-dimensional (3D) model of the bone from the at least one medical image,
 - 30 identify a region of the bone with a bone defect,
- an orthopaedic prosthesis design module configured to:
 - generate a defect reconstruction model,
 - generate a 3D prosthesis model that corresponds to the defect reconstruction model, wherein the 3D prosthesis model is patient specific.

- 35 In one example the orthopaedic prosthesis design module is configured to export the 3D prosthesis model for 3D printing an prosthesis that corresponds in shape and configuration to the 3D prosthesis model based.

- 40 In one example the reconstruction model is a 3D model of a portion of a bone that corresponds to a normal bone without the bone defect.

In one example the reconstruction model is indicative of a prosthesis that can be attached to the bone in the region. The reconstruction model may be similar in shape, size and configuration as a prosthesis (i.e., an implant) that can be attached to the patient's bone.

The orthopaedic prosthesis may be an implant that is implanted into a patient. The implant i.e., orthopaedic prosthesis may be surgically attached to a bone of a patient once the bone defect is surgically removed. The implant i.e., prosthesis can allow the surgically modified bone to heal and function as normal once the prosthesis that is generated by the method described herein is surgically attached to the bone i.e., implanted into the patient.

In one example, the system comprises a user interface, e.g., a display screen. In one example the reconstruction model may be presented on a user interface on the 3D bone model thereby illustrating how a corrected bone should look.

In one example the segmentation module is configured to:
perform volumetric segmentation of the medical image,
generate the 3D model of the bone based on the volumetric segmentation.

In one example, the system comprises:
a medical image pre-processing module, wherein the image pre-processing module is configured to:
pre-process the received at least one medical image by normalization and/or standardization, and;
wherein the segmentation module is configured to:
extract contextual information from the at least one medical image,
reconstruct spatial details via up-sampling,
generate the 3D model of the bone based on the contextual information and the reconstructed spatial details.

In one example the system comprising a surgical planning module, the surgical planning module is configured to: determine a surgical pathway to remove the bone defect and present the determined surgical pathway on a user interface.

In one example the surgical planning module is configured to:
identify a size and shape of a cut to remove the bone defect,
present the identified cut on a user interface,
determine a position for the reconstruction model to correct the bone defect,
determine a fixation arrangement to position an prosthesis on the bone to correct the bone defect.

In one example the orthopaedic prosthesis design module is configured to generate the 3D prosthesis model based on the identified cut, the reconstruction model and the fixation arrangement.

In one example the 3D prosthesis model is customized in shape and configuration to match the patient's bone, such that the 3D prosthesis model is patient specific.

In one example the system comprising a machine learning model, the machine learning model comprising:

- an encoder path configured to capture contextual information,
- a decoder path adapted to reconstruct spatial information,
- 5 skip connections linking corresponding encoder and decoder layers, and;
- wherein the segmentation module and the orthopaedic prosthesis design module incorporated as part of the machine learning module.

10 In one example the encoder path comprising a plurality of layers, and the decoder path comprising a plurality of layers, and the machine learning model is a 3D U-net model.

In one example the 3D U-net model comprising an encoder path, a decoder path and skip connections linking corresponding encoder and decoder layers, wherein the encoder path is adapted to capture contextual information and the decoder path adapted to reconstruct spatial information.

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In one example the encoder path comprises a plurality of 3D convolution layers, each layer is followed by or includes batch normalization and ReLU activation. Optionally, the encoder path may include average pooling after each convolution layer.

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In one example, the system comprises a 3D printer. The 3D printer is configured to receive the exported 3D prosthesis model and print an orthopaedic prosthesis corresponding to the 3D prosthesis model.

25 According to a further aspect, the present invention provides a system for automated orthopaedic prosthesis design comprising:

- a computing apparatus comprising a processor and a memory unit, the processor and memory unit being operatively coupled to each other,
- the memory unit adapted to store instructions which, when executed by the processor cause the computing apparatus to:
- 30 receive at least one medical image of a bone of a patient,
- generate a three-dimensional (3D) model of the bone from the at least one medical image,
- identify a region of the bone with a bone defect,
- 35 generate a defect reconstruction model,
- generate a 3D prosthesis model that corresponds to the defect reconstruction model, wherein the 3D prosthesis model is patient specific i.e., customised for the patient.

40 In one example the computing apparatus may be configured to perform one or more functions or steps defined in the method statements earlier herein.

In accordance with an aspect, the present invention relates to an artificial intelligence (AI) assisted orthopaedic prosthesis design system. The system may also be used for surgical planning. The system comprises an AI-assisted module that focuses on patient-specific orthopaedic prosthesis (i.e. prosthesis) design. Employing AI

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algorithms, this module utilizes a comprehensive range of complex data, including high-resolution medical imaging, biomechanical dynamics, and detailed patient medical histories. By analysing this information, the system generates precise three-dimensional models that conform to the patient's anatomical contours, facilitating the creation of orthopaedic prosthesis (i.e. prosthesis) that seamlessly restore optimal function.

In accordance with an aspect, the present invention relates to an artificial intelligence assisted orthopaedic prosthesis design and surgical planning system. In one example the system provides a method for medical image segmentation and a method for bone model defect simulation. In one example the system may include a machine learning algorithm for bone defect repair prediction and a machine learning algorithm for surgical implant design with fixation plate. In one example the system is a computer-implemented system for real-time monitoring and adjustment of orthopaedic prosthesis functionality. In one example there is a method for personalized surgical planning based on patient-specific anatomical and functional data. In one example there is provided a method for optimizing prosthesis material selection based on patient-specific biomechanical characteristics. In one example the system is adapted to implement a machine learning algorithm for optimizing surgical incision and implant placement locations in orthopaedic procedures.

The term “comprising” (and its grammatical variations) as used herein are used in the inclusive sense of “having” or “including” and not in the sense of “consisting only of”.

The term “medical image” as used herein refers to 2D image of a patient’s bone or a part of a patient’s anatomy. The medical image may be a CT scan or X-ray or other suitable image. Optionally, each medical image may comprise multiple 2D views of a patient’s bone or a part of a patient’s anatomy.

The term “prosthesis” or “orthopaedic prosthesis” defines a type of orthopaedic device that is connected or installed on or in a bone to correct a bone defect or return a bone to a normal shape if a bone defect is surgically removed. The terms may be interchangeably used to define the element

BRIEF DESCRIPTION OF THE DRAWINGS

5 Embodiments of the present invention will now be described, by way of example, with reference to the accompanying drawings in which:

Figure 1 illustrates an embodiment of a system for orthopaedic prosthesis design.

10 Figure 2 illustrates a schematic diagram of a computing apparatus that implements a system for orthopaedic prosthesis design.

Figure 3 illustrates a further embodiment of a system for orthopaedic prosthesis design.

15 Figure 4 illustrates an example of a 3D U-net model used for automated orthopaedic prosthesis design.

Figure 5 illustrates an embodiment of an automated method for orthopaedic prosthesis design.

20 Figure 6 illustrates another embodiment of an automated method for orthopaedic prosthesis design.

Figure 7 illustrates sub method steps of pre-processing the images.

25 Figure 8 illustrates sub method steps for the step of extracting contextual information.

Figure 9 illustrates sub method steps for the step of determining a surgical pathway.

30 Figure 10 illustrates a method of training a machine learning model for automated orthopaedic prosthesis design.

Figure 11 illustrates examples of training data to train the 3D U-net model of Figure 4.

35 Figure 12 illustrates an output of the 3D U-net model as compared to a ground truth and an input image.

Figure 13 illustrates a comparison of the 3D bone models from the 3D U-net model as compared to ground truth bone models.

40 Figure 14 illustrates a table of quantitative results of training the 3D U-net model.

Figures 15 to 21 illustrate operation of a system and method for automated prosthesis design.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

Referring to Figure 1, an embodiment of the present invention is illustrated. This
5 embodiment is arranged to provide a system 100 for automated orthopaedic prosthesis
design comprising: a segmentation module 102, the segmentation module configured
to: receive at least one medical image of a bone of a patient, generate a three
dimensional (3D) model of the bone from the at least one medical image, and identify
a region of the bone with a bone defect; and an orthopaedic prosthesis design module
10 104 configured to: generate a defect reconstruction model, generate a 3D prosthesis
model that corresponds to the defect reconstruction model, wherein the 3D prosthesis
model is patient specific. The prosthesis model (i.e., implant model) corresponds to a
structure or component that is used to correct a bone defect.

15 The system is advantageous because it provides an automated system to segment
medical images of a bone of a patient and automatically generate a customised
prosthesis to correct a bone defect or provide a correcting element that is attached to a
bone once a bone defect is surgically removed.

20 In one example the orthopaedic prosthesis design module 104 is configured to export
the 3D prosthesis model for 3D printing an prosthesis that corresponds in shape and
configuration to the 3D prosthesis model based. The system may comprise a 3D printer
110 that is operatively coupled to the orthopaedic prosthesis design module by a wired
connection or a wireless connection. The 3D printer 110 may be configured to receive
25 a 3D prosthesis model. The 3D prosthesis model may be exported into an appropriate
file format that can be used to 3D print an orthopaedic prosthesis that corresponds to
the 3D prosthesis model. The 3D printer 110 may be configured to print the orthopaedic
prosthesis.

30 The 3D printer 110 may be configured to print the prosthesis out of a suitable
biocompatible material such as titanium or ceramic or other suitable biocompatible
material. The orthopaedic prosthesis (i.e., orthopaedic implant) that is 3D printed may
be coupled to a bone to correct a bone defect that is identified. The prosthesis i.e.,
orthopaedic implant maybe surgically installed in the patient's bone once the bone
35 defect is removed.

The segmentation module 102 and the orthopaedic prosthesis design module 104 may
be operatively coupled to each other. The segmentation module 102 is configured to
receive at least one medical image, but preferably a plurality of medical images 10 as
40 an input. The segmentation module 102 may receive multiple medical images of a
patient's bone. The segmentation module 102 may receive a plurality medical images
of a lower limb bone e.g., a femur, tibia or fibula or other lower limb bone. In one
example, the medical images may be CT scan images.

The segmentation module 102 is configured to process the received medical images to segment the medical images and generate a 3D model of the bone. In particular, the segmentation module 102 is configured to perform volumetric segmentation of the medical images. The segmentation module 102 is configured to generate a 3D model of the bone based on volumetric segmentation. The 3D bone model is reconstructed from the segmentation processing of the medical images. The medical images may comprise 2D images from different views e.g., anterior, posterior, lateral etc. The 3D model is generated from the 2D views and is indicative of the lower bone visible in the medical images.

The segmentation module 102 is further configured to identify a bone defect in the bone. The bone defect may be identified at a region of interest in the bone, and the bone defect may be highlighted. The segmentation model 102 is adapted to output a 3D bone model with the bone defect shown in the 3D model.

The system 100 may comprise a user interface 112. The user interface 112 may be screen or display e.g., a LCD screen or LED screen. The 3D bone model may be displayed on the user interface after automatic segmentation of the plurality of medical images. Additionally, the 3D prosthesis model (i.e., implant model) and reconstruction model may be displayed after each is generated. In one example the defect reconstruction model is a 3D model of a portion of a bone that corresponds to a normal bone without the bone defect.

In the illustrated form shown in Figure 1, the system 100 comprises a medical image pre-processing module 106. The medical image pre-processing module 106 is configured to receive the plurality of medical images 10. The pre-processing module 106 is further configured to pre-process the received medical images (i.e., the at least one medical image) by normalisation and/or standardisation. The pre-processing module 106 is adapted to process the medical images prior to the segmentation module processes the images.

The segmentation module 102 module is further configured to extract contextual information and reconstruct spatial information from the plurality of medical images. The spatial details may be reconstructed by up-sampling. The segmentation module 102 is further configured to generate a 3D model of the bone (i.e., 3D bone model) based on the contextual information and the reconstructed spatial details. The 3D bone model is an accurate 3D representation of the bone in the medical images.

The system 100 involves pre-processing input data (e.g., the medical images), applying data augmentation techniques and outputting a 3D model of the bone. The system 100 provides a robust tool for precise segmentation of patient anatomy from the medical images which is advantageous for medical practitioners. The system 100 is also advantageous because it provides for a tool that allows for faster and more efficient segmentation of medical images as compared to the current manual practice.

In one example the system comprising a surgical planning module, the surgical planning module is configured to: determine a surgical pathway to remove the bone defect and present the determined surgical pathway on a user interface.

5 The example form of the system 100, as shown in Figure 1 further comprises a surgical planning module 108. The surgical planning module 108 is configured to identify a location, size and shape of a cut to remove the identified bone defect. The identified cut i.e., the location, size and shape of the cut may be presented on the user interface 112. The surgical planning module 108 is configured to determine a position for the reconstruction model to correct the bone defect i.e., how and where to position the reconstruction model to fix the bone defect e.g., once the bone defect is cut out.

15 The surgical planning module 108 is further configured to determine a fixation arrangement to position the orthopaedic prosthesis on the bone to correct the bone defect and allow the bone to function normally. The fixation arrangement may include screws or bolts or adhesives or any other suitable manner to affix the prosthesis onto the bone. The surgical planning module 108 may further determine the appropriate surgical path to remove the bone defect and position the reconstruction model and prosthesis into the gap or void left after removing the bone defect.

20 In one example, the location, size and shape of the cut may be displayed on the user interface 112. Additionally, the reconstruction model position and the fixation arrangement may also be displayed once determined by the surgical planning module 108.

25 In an alternative example, the bone defect may be fixed by attaching a prosthesis to the bone. In this alternative form, the surgical planning module 108 may further calculate the best location and manner to fix the prosthesis onto the bone to correct the bone defect.

30 The orthopaedic prosthesis design module 104 may be configured to generate the 3D prosthesis model based on the identified cut, the reconstruction model and the fixation arrangement. The 3D prosthesis model is customized in shape and configuration to match the patient's bone, such that the 3D prosthesis model is patient specific i.e., customised to the patient.

35 In this example embodiment, the modules as described may be implemented by a computing apparatus 200 (i.e., computer) having an appropriate user interface and appropriate other components. The computing apparatus 200 may be implemented by any computing architecture, including portable computers, tablet computers, stand-alone Personal Computers (PCs), smart devices, Internet of Things (IOT) devices, edge computing devices, client/server architecture, "dumb" terminal/mainframe architecture, cloud-computing based architecture, or any other appropriate architecture. The computing device may be appropriately programmed to implement the invention.

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In one example form the modules as described herein may be hardware modules such as ICs or microprocessors that may be operatively coupled to each other. Alternatively, the modules may be software modules that may be implemented on a computing apparatus 200 as described herein. The software modules may be arranged in the architecture shown in Figure 1 and may be operatively coupled. In a further alternative form, the modules may be a combination of hardware and software elements.

Figure 2 illustrates a schematic diagram of a computing apparatus 200 (i.e., computer or computing server) which is arranged to be implemented as an example embodiment of a system for automated orthopaedic prosthesis design. In this embodiment comprises a computing apparatus 200 which includes suitable components necessary to receive, store and execute appropriate computer instructions. The components may include a processor 202 (i.e., processing unit), including Central Processing Unit (CPU), Math Co-Processing Unit (Math Processor), Graphic Processing Unit (GPUs) or Tensor Processing Unit (TPUs) for tensor or multi-dimensional array calculations or manipulation operations, read-only memory (ROM) 204, random access memory (RAM) 206, and input/output devices such as disk drives 208, input devices 210 such as an Ethernet port, a USB port, etc. Display 212 such as a LCD or LED display, or any other suitable display may be part of the computing apparatus 200. Optionally, the display 212 may be remote or separate from the computing apparatus 200. The display 212 may be the user interface 112 or may present the user interface 112.

The computing apparatus 200 may include instructions that may be included in ROM 204, RAM 206 or disk drives 208 and may be executed by the processing unit 202 (i.e., processor). There may be provided one or more communication links 214 which may variously connect to one or more computing devices such as a server, personal computers, terminals, wireless or handheld computing devices, Internet of Things (IoT) devices, smart devices, edge computing devices. At least one of a plurality of communications link may be connected to an external computing network through a telephone line or other type of communications link.

The computing apparatus 200 may include storage devices such as a disk drive 208 which may encompass solid state drives, hard disk drives, optical drives, magnetic tape drives or remote or cloud-based storage devices. The computing apparatus 200 may use a single disk drive or multiple disk drives, or a remote storage service. The computing apparatus 200 may also have a suitable operating system which resides on the disk drive or in the ROM of the computing apparatus 200.

The computing apparatus may further comprise one or more databases 220 adapted to store one or more pieces of data. The databases may store bone model data. The one or more databases may store input images received and may also store the 3D bone models generated by the system 100.

The computer or computing apparatus 200 may also provide the necessary computational capabilities to operate or to interface with a machine learning network,

such as a neural networks, to provide various functions and outputs. The neural network may be implemented locally, or it may also be accessible or partially accessible via a server or cloud-based service. The machine learning network may also be untrained, partially trained or fully trained, and/or may also be retrained, adapted or updated over
5 time. The computing apparatus may comprise one or more GPUs being operatively coupled to the CPU (i.e., processor). The computing apparatus may comprise additional hardware elements operatively coupled to the CPU and/or the GPU to provide the computing apparatus components needed to implement a machine learning network or machine learning model. The learning network or model may be stored in a memory
10 unit e.g., ROM.

Figure 3 illustrates an alternative embodiment of a system 300 for orthopaedic prosthesis design. The system 300 comprises a computing apparatus 302. The computing apparatus comprises a processor and a memory unit, the processor and
15 memory unit being operatively coupled to each other. The memory unit is adapted to store instructions which, when executed by the processor cause the computing apparatus to: receive at least one medical image of a bone of a patient, generate a three dimensional (3D) model of the bone from the at least one medical image, identify a region of the bone with a bone defect, generate a defect reconstruction model,
20 generate a 3D prosthesis model that corresponds to the defect reconstruction model, and; wherein the 3D prosthesis model is patient specific i.e., customised for the patient.

The computing apparatus 302 may be the same as computing apparatus 200. The computing apparatus 302 is configured to stored and execute a machine learning model or AI model or a machine learning network that is configured to: receive at least one
25 medical image of a bone of a patient, generate a three dimensional (3D) model of the bone from the at least one medical image, identify a region of the bone with a bone defect, generate a defect reconstruction model, generate a 3D prosthesis model that corresponds to the defect reconstruction model, and; wherein the 3D prosthesis model is patient specific i.e., customised for the patient. The functions of the various modules described earlier may be executed by the machine learning model 400. The machine learning model 400 is trained to automatically segment medical images, generate a 3D bone model, identify a bone defect and generate an orthopaedic prosthesis model that can be implanted to fix a bone after the bone defect is removed. The machine learning
30 model 400 may executed by a processing unit 202 and may be stored on a memory unit 304.

The system 300 may further comprise a 3D printer 310 that is operatively coupled to the computing apparatus 302. The computing apparatus 302 may transmit the orthopaedic prosthesis model generated by the machine learning model 400 to the 3D
40 printer 310. The 3D printer 310 may be adapted to 3D print an orthopaedic prosthesis (i.e., an orthopaedic implant) based on the exported prosthesis model generated by the machine learning network 400 (i.e., AI model 400).

The system 300 may also include a user interface 312 that may display the 3D bone model, and prosthesis model on it. The user interface 312 may be a display like display 212.

5 Figure 4 illustrates an example embodiment of a machine learning model 400 (or machine learning network or AI model) that is stored in a memory unit of the computing apparatus 302 or 200 and executed by a processing unit of the computing apparatus. Referring to Figure 4, the machine learning model 400 comprises an encoder path 402 configured to capture contextual information, a decoder path 404 adapted to reconstruct spatial information, and skip connections linking corresponding encoder and decoder layers.
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The machine learning model is advantageous because it automatically processes medical images and generates a custom prosthesis model that can be printed. This provides time savings on image segmentation, provides a more accurate prosthesis model and can improve cost effectiveness and result in faster creation of prostheses (i.e., implants).
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In one example, the machine learning model 400 may be a 3D U-net model. The 3D U-net model is a “U” shaped model. The encoder 402 path is preferably a contracting path and the decoder path 404 is preferably an expanding path. The encoder path 402 comprises a plurality of layers, such as for example convolution layers. The decoder path 404 comprising a plurality of layers e.g., convolution layers. The convolution layers may have varying sizes i.e., varying dimensions.
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Each layer in the encoder path 402 may be followed by or includes batch normalization and ReLU activation. Optionally, the encoder path 402 may include average pooling after each convolution layer. As shown in Figure 4, the machine learning model 400 may include seven convolution layers in the encoder path 402 and two convolution layers in the decoder path 404. The skip connections link corresponding encoder and decoder paths. In one example, skip connections assist with backward flow of data. In one example the input data fed into the model may comprise 3D CT scans. The 3D CT scans may be pre-processed prior to feeding into the 3D U-net model by normalisation and standardisation.
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Figure 5 illustrates example embodiment of method 500 for automated orthopaedic prosthesis design. The method comprises a plurality of steps. Step 502 comprises receiving at least one medical image of a bone of a patient. Preferably a plurality of medical images are received. Step 504 comprises generating a three-dimensional (3D) model of the bone from the at least one medical image. Step 506 comprises identifying a region of the bone with a bone defect. Step 508 comprises generating a defect reconstruction model. Step 510 comprises generating a 3D prosthesis model (i.e., 3D prosthesis model) that corresponds to the defect reconstruction model, wherein the 3D prosthesis model is patient specific i.e., customised to the patient and the bone defect suffered by the patient.
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The method 500 may comprise the additional step 512 of exporting the 3D prosthesis model for 3D printing an orthopaedic prosthesis that corresponds in shape and configuration to the 3D prosthesis model based. Optionally, the method 500 may
5 comprise the step of 3D printing an orthopaedic prosthesis based on the exported 3D model.

Figure 6 illustrates an example embodiment of method for automated orthopaedic prosthesis design. The method commences at step 602. Step 602 comprises receiving
10 a plurality of medical images of a patient's bone that has a bone defect. The bone may be a lower limb bone e.g., a weight bearing bone. Step 604 comprises performing volumetric segmentation of the received medical images. Step 606 comprises generating a 3D model of the bone based on the contextual information and reconstructed spatial details. The 3D model of the bone may be generated based on
15 the volumetric segmentation.

Step 608 is performed once a 3D model of the bone is generated. Step 608 comprises identifying a bone defect in the 3D bone model. Step 610 comprises determining a surgical pathway to remove the bone defect. The surgical pathway may be displayed
20 or presented on the user interface 112 or display 212 of the computing apparatus 200.

Step 612 which follows on from step 610. Step 612 comprises generating a defect reconstruction model. The reconstruction model is a 3D model of the shape required to attach to the bone to return the shape of the bone to a normal bone shape once the
25 defect is removed. The reconstruction model may be displayed on the user interface 112 or display 212. Step 614 comprises generating a 3D prosthesis model (i.e., implant model). The 3D prosthesis model is generated based on the identified cut, reconstruction model and the fixation arrangement. The 3D prosthesis model (i.e. implant model) may be patient specific i.e., customised to the patient and customised
30 to address the specific bone defect the patient is suffering from. Step 616 comprises exporting the 3D prosthesis model.

The step of volumetric segmentation at step 604 comprises the additional steps. The sub method steps of pre-processing the images are shown in Figure 7. Step 620
35 comprises pre-processing the received medical images by normalisation and/or standardisation. In one example a batch normalisation operation may be performed on the received images. Step 622 comprises extracting contextual information from the medical images. Step 624 comprises reconstructing spatial details via up sampling.

In one example the step of extracting contextual information at step 622 comprises the additional steps as shown in Figure 8. Step 630 comprises performing 3D convolutions
40 on the received medical images. Step 632 comprises performing batch normalization on the received images and/or the 3D convolutions and step 634 comprises performing ReLU activation after each convolution process.

45

The step of determining a surgical pathway 610 comprises additional sub steps as shown in Figure 9. Referring to Figure 9, step 640 comprises identifying a cut (or other surgical operation) to remove the bone defect from the bone. Identifying the cut includes determining the size and shape of a cut to remove the bone defect. Step 642 comprises presenting the identified cut on a user interface 112 e.g. the display 212 to illustrate the proposed cut to a medical professional. Step 644 comprises determining a position for the reconstruction model to correct the bone defect. Step 646 comprises determining a fixation arrangement to position and attach an prosthesis (i.e., an implant) on the bone to correct the bone defect.

The method is advantageous because it provides an improved and automated method for segmenting new patient medical images. The automated segmenting method is quicker than a manual method that is currently used. The method is advantageous because it enables production of custom prosthesis (i.e., orthopaedic implant) that fits better with a patient's anatomy, resulting in reduced surgery times, improved prosthesis fit and better post operative results.

The method 600 may optionally include the step of 3D printing an orthopaedic prosthesis based on the prosthesis model. The prosthesis may be printed from a suitable biocompatible material. The methods 500 and 600 may be particularly suited for generating an orthopaedic prosthesis design (i.e., an implant design) that is suitable for use on lower limbs of a patient. The methods 500 and 600 may be executed by the computing apparatus 200. In one example, the steps of method 500 or method 600 a machine learning model executed on the computing apparatus 200. For example, the method 500 and 600 may be executed by a 3D U-net model (e.g. like the model 400 shown in Figure 4) that is stored on and executed by a computing apparatus 200.

In one example form, the computing apparatus 200 may comprise a computer program comprising instructions which, when the program is executed by a computer, cause the computer to carry out the steps of method 500 or method 600 as described.

In one example form, the system for orthopaedic prosthesis design comprises a computer-readable medium comprising instructions which, when executed by a computing apparatus e.g., apparatus 200, cause the computing apparatus to carry out the steps of method 500 or method 600.

Figure 10 illustrates an example, of a computer implemented method of training 700 the machine learning model 400 e.g. the 3D U-net model used to segment medical images and generate an orthopaedic prosthesis model. The training method commences at step 702. Step 702 comprises receiving a training dataset comprising a plurality of medical images with a bone, bone defect and ground truth segmentations. The training dataset may include input data and output data. The input data comprises a plurality of images or models with one or more bone defects. The output data comprises a plurality of images or models of normal bones. The input data and output data may be fed through the U-net model 400 to train the model.

Step 704 comprises feeding the training dataset through convolution layers of the 3D U-net model. Step 706 comprises optimising model parameters using combination of Dice coefficient loss and binary cross entropy. Step 708 comprises enhancing generalisation by applying one or more variability techniques. Step 710 comprises monitoring performance of the model based on a validation dataset to ensure convergence and reduce overfitting.

The encoder path during the training uses 3D convolutions, batch normalisation and ReLU activation. The decoder path during training performs up-sampling operations and utilises skip connections for detail preservation. The network parameters were optimised using a combination of Dice coefficient loss and binary cross entropy. Additionally, the training data was augmented using techniques such as random rotations, elastic deformations and intensity variations to enhance generalisation of the training data and model. The 3D U-net model 400 may be trained using supervised learning.

Figure 11 illustrates the training data and how it is prepared. The training data may be prepared by using 3D bone models which are generated either manually or by another suitable operation. Some of the 3D bone models have a section manually removed to simulate a bone defect. The original unaltered 3D bone models were grouped as output data and the models with the simulated bone defects were input data for training the 3D U-net model.

The training data batch sizes were selected for GPU memory, with batches containing multiple 3D models. Performance of the model 400 was monitored on a validation data set to ensure convergence and to avoid overfitting. The model training implemented an early stopping mechanism based on validation metrics. The training of the 3D U-net model 400 may be stopped based on validation metrics. The trained model 400 accurately segments new input images for 3D reconstruction of bones and defect regions.

Figure 12 illustrates an example comparison of the model output with ground truth. Referring to Figure 12 the input image 800 resulted in the predicted segmented result 802, which was compared with ground truth 804. The predicted data 802 is very close to the ground truth 804. This shows the U-net model as per the present invention is trained adequately. Figure 13 shows further outputs of the 3D bone models generated by the U-net model 400 compared to the ground truth. The 3D model on the left of each pane in figure 13 is the output and the right 3D model is the ground truth. Figure 13 illustrates the 3D U-net model 400 described herein provides accurate segmentation and 3D reconstruction of bones from 2D input medical images. Figure 14 illustrates quantitative results of training the U-net model 400 as per the present invention. The results show the Dice Similarity Coefficient (DSC), Intersection over Union (IoU) and Hausdorff Distance (HD) for the model 400 performance.

Figures 15 to 21 illustrate operation of a system and method for automated prosthesis design. The illustrated operation i.e. implementation may be performed by the U-net model 400 described earlier. Figure 15 illustrates importing medical images 902, 904, 906. A bone model 908 is generated by the 3D U-net from the medical images (e.g., CT scans). Referring to Figure 16, a region of interest 910 having a bone defect is identified. The U-net model 400 may create a cut 912 and present the cut on the user interface (e.g., interface 112), as shown in Figure 17. The cut 912 being indicative of the surgical operation to remove the bone defect. As shown in Figure 18, the U-net model 400 automatically generates a reconstruction model 914, i.e., the U-net model 400 performs automatic defect reconstruction. The reconstruction model 914 is presented as fitting into the cut 912 to return the bone to a normal shape. The U-net model determines a fixation structure 916 to mount a prosthesis (i.e., implant), as shown in Figure 19. As shown in Figure 19, the fixation structures are screws 916 and four screw placements are generated by the U-net model 400. The U-net model 400 is adapted to automatically generate a prosthesis model 918 (i.e. implant model), as shown in Figure 20. The prosthesis may be shaped to fit into the cut. The implant model 918 may be exported e.g., into a 3D CAD file as shown in Figure 21.

The system and method for automated orthopaedic prosthesis design provides an improvement in surgical outcomes and implant design. The U-net model may continually learn and refine designs based on learning from outcome data leading to more efficient and cost effective and personalised orthopaedic care. The system and method combines deep learning with manufacturing techniques to create customised prosthesis (i.e. implants). The system and method further lead to reduced surgery times and enhance the prosthesis fit and post operative results. The AI model used may continually learn and improve precision and cost effectiveness.

An additional example of a system for automated orthopaedic prosthesis design will be described. In this example the system integrates artificial intelligence (AI) to deliver highly personalized solutions for orthopaedic prosthesis design and surgical planning, specifically tailored to each patient's unique anatomical requirements.

In this example the system may comprise an AI-assisted module that focuses on patient-specific orthopaedic prosthesis/implant design. Employing AI algorithms, this module utilizes a comprehensive range of complex data, including high-resolution medical imaging, biomechanical dynamics, and detailed patient medical histories. By analysing this information, the system generates precise three-dimensional models that conform to the patient's anatomical contours, facilitating the creation of orthopaedic prosthesis (i.e., implant) that seamlessly restore optimal function.

The system may also include an AI-assisted medical image segmentation module, which employs advanced image processing techniques. This module enables accurate segmentation of medical images into distinct anatomical regions, thereby facilitating the creation of highly accurate three-dimensional models. By enhancing the accuracy and

efficiency of the overall prosthesis design process, this AI-driven segmentation module significantly contributes to the system's effectiveness.

5 The system also integrates a pre-operative surgical planning software module. This module utilizes predictive models to anticipate the surgical pathway, enabling surgeons to simulate and plan procedures with exceptional precision. By conducting comprehensive pre-operative simulations, potential challenges are identified, and the most effective surgical strategies can be devised based on the patient's individual prosthesis design and physiological profile. This AI-assisted surgical planning module
10 empowers surgeons to make informed decisions, leading to improved surgical outcomes, enhanced patient satisfaction, and accelerated recovery.

The system may include an AI self-learning mechanism. Through iterative learning, the system continuously refines its predictive accuracy and design precision by assimilating
15 post-operative results. This self-improvement process further enhances the system's efficacy and reliability, reinforcing its position in orthopaedic care.

The system enhances the function of the implants and aims to substantially decrease the probability of implant-related complications.

20 In this example, the system may include a dynamic, interactive planning module capable of accommodating the variable nature of surgical operations. This module enhances the surgeon's readiness, leading to a more streamlined surgical process that is both efficient and accurate.

25 The system integrates patient-specific anatomical data with advanced predictive analytics, thereby diminishing the risks associated with misalignment and other surgical difficulties. This integration helps reducing the frequency of postoperative complications and the subsequent need for revision surgeries.

30 A benefit of the described systems is the reduction in patient recovery time, as the precisely designed prostheses/implants and well-planned surgical procedures contribute to a decrease in hospitalisation duration and a faster recover of daily activities for patients. The system's streamlined approach to surgery reduces the time spent in
35 the operating theatre and minimises the consumption of medical resources, resulting in economic savings for healthcare institutions and patients.

The A.I. system may have a continuous improvement mechanism, wherein an artificial intelligence module learns from each surgical intervention, refining its algorithms. This
40 mechanism ensures the application of cutting-edge techniques in both the design of surgical implants and the planning of surgical procedures. The system may be configured to facilitate the collection and analysis of postoperative data, advancing the knowledge of surgical implant performance and patient outcomes.

In this additional example, the system for automated orthopaedic prosthesis design introduces a higher degree of personalisation, predictive precision, and efficiency, along with advanced training capabilities and continuous data-driven improvement.

5 Although not required, the embodiments described with reference to the Figures can be implemented as an application programming interface (API) or as a series of libraries for use by a developer or can be included within another software application, such as a terminal or personal computer operating system or a portable computing device operating system. Generally, as program modules include routines, programs, objects,
10 components and data files assisting in the performance of particular functions, the skilled person will understand that the functionality of the software application may be distributed across a number of routines, objects or components to achieve the same functionality desired herein.

15 It will also be appreciated that where the methods and systems of the present invention are either wholly implemented by computing system or partly implemented by computing systems then any appropriate computing system architecture may be utilised. This will include stand alone computers, network computers and dedicated hardware devices. Where the terms "computing system" and "computing device" are
20 used, these terms are intended to cover any appropriate arrangement of computer hardware capable of implementing the function described.

Any reference to prior art contained herein is not to be taken as an admission that the information is common general knowledge, unless otherwise indicated.

25 Also, it is noted that example forms may be described as a process that is depicted as a flowchart, a flow diagram, a structure diagram, or a block diagram. Although a flowchart may describe the operations as a sequential process, many of the operations can be performed in parallel or concurrently. In addition, the order of the operations
30 may be rearranged. A process is terminated when its operations are completed. A process may correspond to a method, a function, a procedure, a subroutine, a subprogram, etc., in a computer program. When a process corresponds to a function, its termination corresponds to a return of the function to the calling function or a main function.

35 One or more of the components and functions illustrated the figures may be rearranged and/or combined into a single component or embodied in several components without departing from the scope of the invention. Additional elements or components may also be added without departing from the scope of the invention. Additionally, the features
40 described herein may be implemented in software, hardware, as a business method, and/or combination thereof.

It will be appreciated by persons skilled in the art that numerous variations and/or modifications may be made to the invention as shown in the specific embodiments
45 without departing from the spirit or scope of the invention as broadly described.

The present examples and forms are, therefore, to be considered in all respects as illustrative and not restrictive.

CLAIMS

1. A computer-implemented method for automated orthopaedic prosthesis design, comprising:
 - 5 receiving at least one medical image of a bone of a patient,
 - generating a three-dimensional (3D) model of the bone from the at least one medical image,
 - identifying a region of the bone with a bone defect,
 - generating a defect reconstruction model,
 - 10 generating a 3D prosthesis model that corresponds to the defect reconstruction model, wherein the 3D prosthesis model is patient specific.
2. The method of claim 1, further comprising the additional step of exporting the 3D prosthesis model for 3D printing an orthopaedic prosthesis that corresponds in shape and configuration to the 3D prosthesis model based.
 - 15
3. The method of claim 1, wherein the reconstruction model is a 3D model of a portion of a bone that corresponds to a normal bone without the bone defect.
4. The method of claim 1, further comprising the additional steps of:
 - 20 performing volumetric segmentation of the medical image,
 - generating the 3D model of the bone based on the volumetric segmentation.
5. The method of claim 4, wherein the step of performing volumetric segmentation comprises the additional steps of:
 - 25 pre-processing the received at least one medical image by normalization and/or standardization,
 - extracting contextual information from the at least one medical image,
 - 30 reconstructing spatial details via up-sampling,
 - generating the 3D model of the bone based on the contextual information and the reconstructed spatial details.
6. The method of claim 5, wherein the step of extracting contextual information comprises the steps of:
 - 35 performing 3D convolutions on the at least one medical image,
 - performing batch normalization on the at least one image and/or the 3D convolutions, and;
 - performing ReLU activation.
 - 40
7. The method of claim 1, further comprising the additional step of determining a surgical pathway to remove the bone defect and presenting the determined surgical pathway on a user interface.

8. The method of claim 1, wherein the step of determining a surgical pathway comprises the additional steps of:
identifying a cut to remove the bone defect, wherein identifying the cut includes determining the size and shape of a cut to remove the bone defect,
5 presenting the identified cut on a user interface,
 determining a position for the reconstruction model to correct the bone defect,
 determining a fixation arrangement to position a prosthesis on the bone to correct the bone defect.
- 10 9. The method of claim 8, wherein the 3D prosthesis model is generated based on the identified cut, reconstruction model and the fixation arrangement.
- 15 10. The method of claim 3, wherein the 3D prosthesis model is customized in shape and configuration to match the patient's bone, such that the 3D prosthesis model is patient specific.
- 20 11. A machine learning model for automated orthopaedic prosthesis design, in particular for use in the method of any one or more of claims 1-10, comprising:
 an encoder path configured to capture contextual information,
 a decoder path adapted to reconstruct spatial information, and;
 skip connections linking corresponding encoder and decoder layers.
- 25 12. The machine learning model of claim 11, wherein the encoder path comprising a plurality of layers, and the decoder path comprising a plurality of layers, and the machine learning model is a 3D U-net model.
- 30 13. A data processing apparatus for automated orthopaedic prosthesis design comprising means for carrying out the method of any one of claims 1-10.
- 35 14. A computer program comprising instructions which, when the program is executed by a computer, cause the computer to carry out the method of any one of claims 1-10.
- 40 15. A computer-readable medium comprising instructions which, when executed by a computer, cause the computer to carry out the method of any one of claims 1-10.
- 45 16. A computer-implemented method of training a machine-learning model for automated orthopaedic prosthesis design, in particular the machine-learning model of claim 11, comprising:
 receiving an input training dataset comprising a plurality of medical images with a bone with a bone defect and ground truth segmentations;
 feeding the input training dataset through convolution layers of the 3D U-net of claim 11,

- optimising model parameters using combination of Dice coefficient loss and binary cross entropy,
enhancing generalisation by applying one or more variability techniques,
and;
5 monitoring performance of the model based on a validation dataset to ensure convergence and reduce overfitting.
17. A training dataset for use in the method of training a machine-learning model of claim 16, comprising:
10 input data, wherein the input data comprises a plurality of images or models with one or more bone defects,
output data, wherein the output data comprises a plurality of images or models of normal bones.
18. A system for automated orthopaedic prosthesis design and construction comprising:
15 a computing apparatus comprising a processor and a memory unit, the processor and memory unit being operatively coupled to each other,
the memory unit adapted to store instructions which, when executed by the
20 processor cause the computing apparatus to perform a method according to any one or more of claims 1 to 10 and 16.
19. A system for automated orthopaedic prosthesis design and construction comprising:
25 a segmentation module, the segmentation module configured to:
receive at least one medical image of a bone of a patient,
generate a three-dimensional (3D) model of the bone from the at least one medical image,
identify a region of the bone with a bone defect,
30 an orthopaedic prosthesis design module configured to:
generate a defect reconstruction model,
generate a 3D prosthesis model that corresponds to the defect reconstruction model, wherein the 3D prosthesis model is patient specific.
35
20. The system of claim 19, wherein the orthopaedic prosthesis design module is configured to export the 3D prosthesis model for 3D printing an orthopaedic prosthesis that corresponds in shape and configuration to the 3D prosthesis model based.
21. The system of claim 19, wherein the reconstruction model is a 3D model of a portion of a bone that corresponds to a normal bone without the bone defect.
22. The system of claim 19, wherein the segmentation module is configured to:
perform volumetric segmentation of the medical image,

generate the 3D model of the bone based on the volumetric segmentation.

23. The system of claim 22, comprising:

5 a medical image pre-processing module, wherein the image pre-processing module is configured to:
pre-process the received at least one medical image by normalization and/or standardization, and;
wherein the segmentation module is configured to:
10 extract contextual information from the at least one medical image,
reconstruct spatial details via up-sampling,
generate the 3D model of the bone based on the contextual information and the reconstructed spatial details.

15 24. The system of claim 19, comprising a surgical planning module, the surgical planning module is configured to: determine a surgical pathway to remove the bone defect and present the determined surgical pathway on a user interface.

20 25. The system of claim 19, wherein the surgical planning module is configured to:
identify a size and shape of a cut to remove the bone defect,
present the identified cut on a user interface,
determine a position for the reconstruction model to correct the bone defect,
25 determine a fixation arrangement to position a prosthesis on the bone to correct the bone defect.

26. The system of claim 25, wherein the orthopaedic prosthesis design module is configured to generate the 3D prosthesis model based on the identified cut, the reconstruction model and the fixation arrangement.

30 27. The system of claim 19, wherein the 3D prosthesis model is customized in shape and configuration to match the patient's bone, such that the 3D prosthesis model is patient specific.

35 28. The system of claim 19, comprising a machine learning model, the machine learning model comprising:
an encoder path configured to capture contextual information,
a decoder path adapted to reconstruct spatial information,
skip connections linking corresponding encoder and decoder layers,
40 and;
wherein the segmentation module and the orthopaedic prosthesis design module incorporated as part of the machine learning module.

29. The system of claim 28, wherein within the machine learning model the encoder path comprising a plurality of layers, and the decoder path comprising a plurality of layers, and the machine learning model is a 3D U-net model.