US012393794B2

(12) **United States Patent**
**Garg et al.**

(10) **Patent No.: US 12,393,794 B2**
(45) **Date of Patent: Aug. 19, 2025**

(54) **VIDEO TRANSLATION PLATFORM**

(71) Applicant: **ACCENTURE GLOBAL SOLUTIONS LIMITED**, Dublin (IE)

(72) Inventors: **Ankur Garg**, Gurgaon (IN); **Rani Gopalakrishnan**, Bangalore (IN); **Shailesh Chaphekar**, Mumbai (IN); **Deepa Dharmit Shah**, Mumbai (IN); **Vipin Bhasin**, Pune (IN); **Pallav Chourey**, Pradesh (IN); **Suraj Khaitan**, Titlagarh (IN); **Anagha Avinash Ghate**, Amaravati (IN); **Kumar Vaibhav**, Noida (IN)

(73) Assignee: **ACCENTURE GLOBAL SOLUTIONS LIMITED**, Dublin (IE)

( * ) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 421 days.

(21) Appl. No.: **17/851,961**

(22) Filed: **Jun. 28, 2022**

(65) **Prior Publication Data**

US 2023/0325611 A1 Oct. 12, 2023

(30) **Foreign Application Priority Data**

| | | |
|---|---|---|
| Apr. 8, 2022 | (IN) | ............................. 202211021128 |
| Apr. 21, 2022 | (IN) | ............................. 202211023590 |

(51) **Int. Cl.**

| | |
|---|---|
| ***G06F 40/58*** | (2020.01) |
| ***G06V 30/19*** | (2022.01) |
| ***G10L 15/26*** | (2006.01) |

(52) **U.S. Cl.**
CPC ........ ***G06F 40/58*** (2020.01); ***G06V 30/19167*** (2022.01); ***G10L 15/26*** (2013.01)

(58) **Field of Classification Search**
None
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

| | | | | |
|---|---|---|---|---|
| 7,117,231 | B2 * | 10/2006 | Fischer ................ | H04N 21/235<br>707/999.203 |
| 2016/0179831 | A1 * | 6/2016 | Gruber .................. | G10L 19/018<br>704/235 |

(Continued)

FOREIGN PATENT DOCUMENTS

| | | | |
|---|---|---|---|
| JP | 2000322077 | A | 11/2000 |
| JP | 2008065653 | A | 3/2008 |

(Continued)

OTHER PUBLICATIONS

Fried et al., "Text-based editing of talking-head video", ACM Trans. Graph, vol. 38, No. 4, 2019 (Year: 2019).*

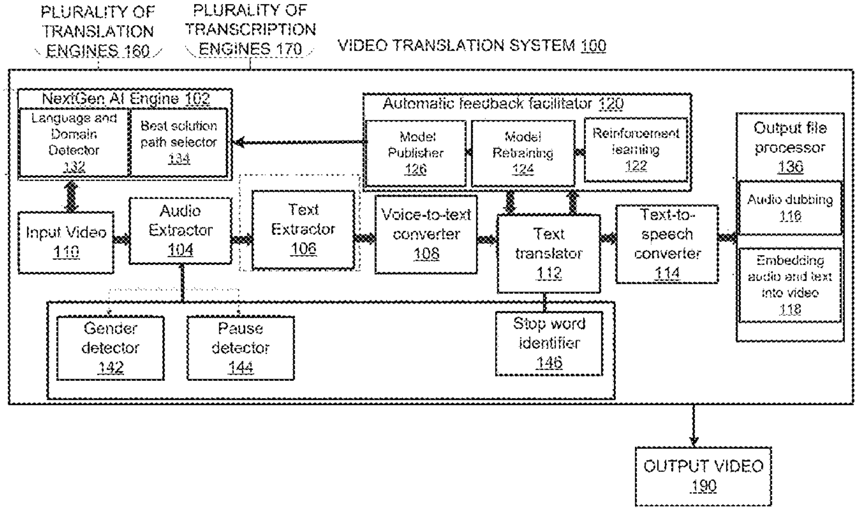
(Continued)

*Primary Examiner* — Nicole A K Schmieder
(74) *Attorney, Agent, or Firm* — Mannava & Kang, P.C.

(57) **ABSTRACT**

A video translation system that generates an output video in a target language which includes a translated/output audio track that runs in synchrony with the video content of a received input video in a source language and further displays translated subtitles corresponding to the translated audio track is disclosed. Upon receiving the input video, the domain of the input video can be identified. A translation engine and a transcription engine are selected based on the domain and the pair of languages corresponding to the input video and the output video. The output audio track is generated using the translation engine and merged with a manipulated video, which runs in synchrony with the output audio track to generate the output video. The transcription engine generates subtitles translated from the source language to the target language for the output video.

**25 Claims, 17 Drawing Sheets**


PLURALITY OF TRANSLATION ENGINES 160
PLURALITY OF TRANSCRIPTION ENGINES 170
VIDEO TRANSLATION SYSTEM 100
NextGen AI Engine 102
Language and Domain Detector 132
Best solution path selector 134
Automatic feedback facilitator 120
Model Publisher 126
Model Retraining 124
Reinforcement learning 122
Output file processor 136
Audio dubbing 116
Embedding audio and text into video 118
Input Video 110
Audio Extractor 104
Text Extractor 106
Voice-to-text converter 108
Text translator 112
Text-to-speech converter 114
Gender detector 142
Pause detector 144
Stop word identifier 146
OUTPUT VIDEO 190

## (56) References Cited

### U.S. PATENT DOCUMENTS

| | | | | |
|---|---|---|---|---|
| 2017/0178623 | A1* | 6/2017 | Shamir | G10L 15/1822 |
| 2020/0169591 | A1* | 5/2020 | Ingel | G10L 13/08 |
| 2022/0036617 | A1 | 2/2022 | Biswas et al. | |
| 2022/0301548 | A1* | 9/2022 | Wintrode | G10L 15/083 |

### FOREIGN PATENT DOCUMENTS

| | | | |
|---|---|---|---|
| JP | 2008158510 | A | 7/2008 |
| JP | 2020034683 | A | 3/2020 |
| JP | 2021511534 | A | 5/2021 |
| JP | 2022017702 | A | 1/2022 |

### OTHER PUBLICATIONS

Yadav et al., “A Multilingual Framework of CNN and Bi-LSTM for Emotion Classification”, 11th ICCCNT, 2020 (Year: 2020).*

Dale Markowitz, “Al Dubs Over Subs? Translating andDubbing Videos with Al”, Feb. 3, 2021, (15 pages).

Unlock A Fresh & High-Quality Traffic Source That 99% Of Your Competition Hasn’t Exploited, Google download date Mar. 28, 2022, https://typestudio.co/use-case/translate-video.

https://vidscribe.in/, Google dowload date Mar. 28, 2022.

“Notice of Decision to Grant Japanese Patent Application No. 2023-062296”, dated Dec. 24, 2024, 2 pages.

* cited by examiner

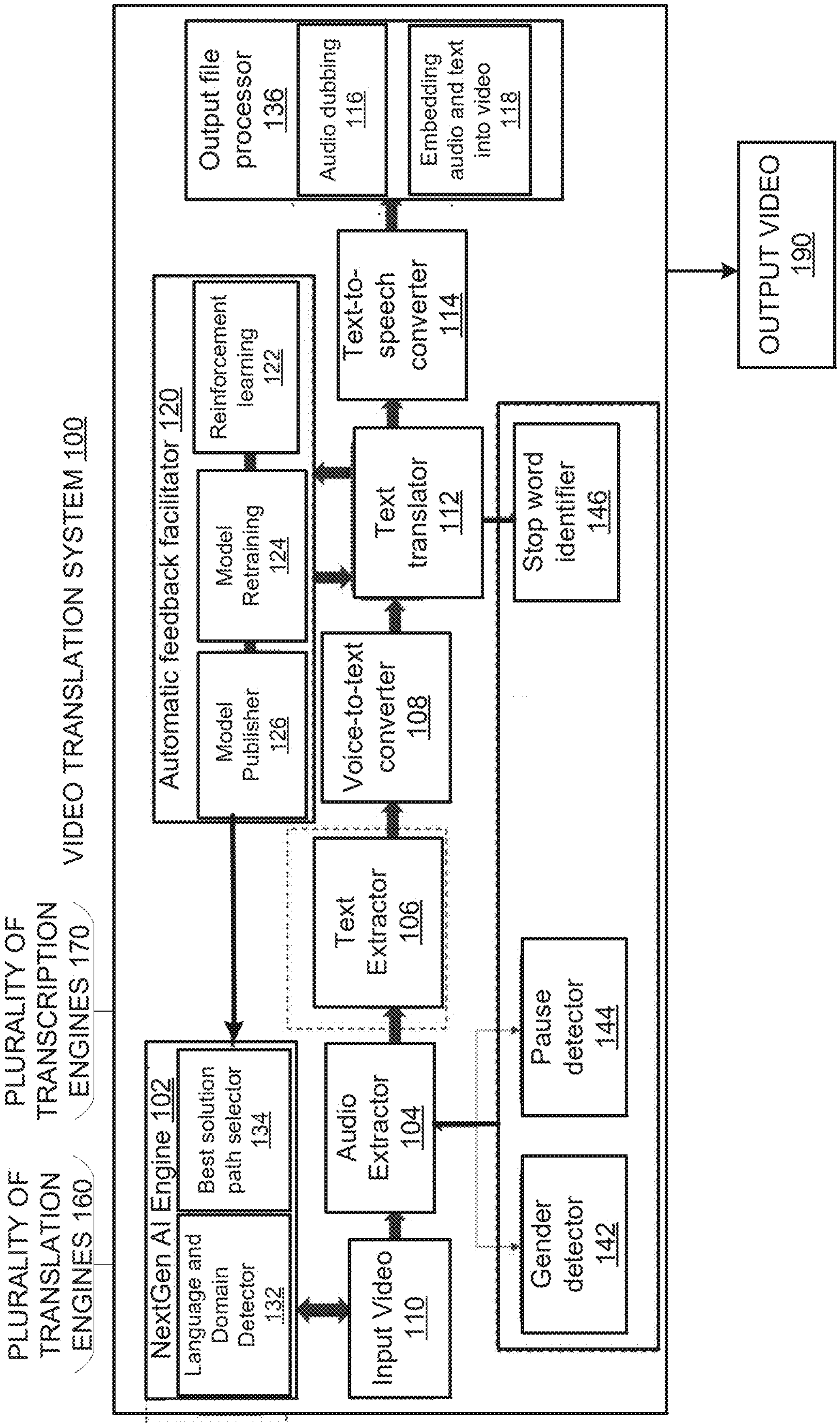

PLURALITY OF TRANSLATION ENGINES 160
PLURALITY OF TRANSCRIPTION ENGINES 170
VIDEO TRANSLATION SYSTEM 100
NextGen AI Engine 102
Language and Domain Detector 132
Best solution path selector 134
Automatic feedback facilitator 120
Model Publisher 126
Model Retraining 124
Reinforcement learning 122
Input Video 110
Audio Extractor 104
Text Extractor 106
Voice-to-text converter 108
Text translator 112
Text-to-speech converter 114
Output file processor 136
Audio dubbing 116
Embedding audio and text into video 118
Gender detector 142
Pause detector 144
Stop word identifier 146
OUTPUT VIDEO 190

FIG. 1A

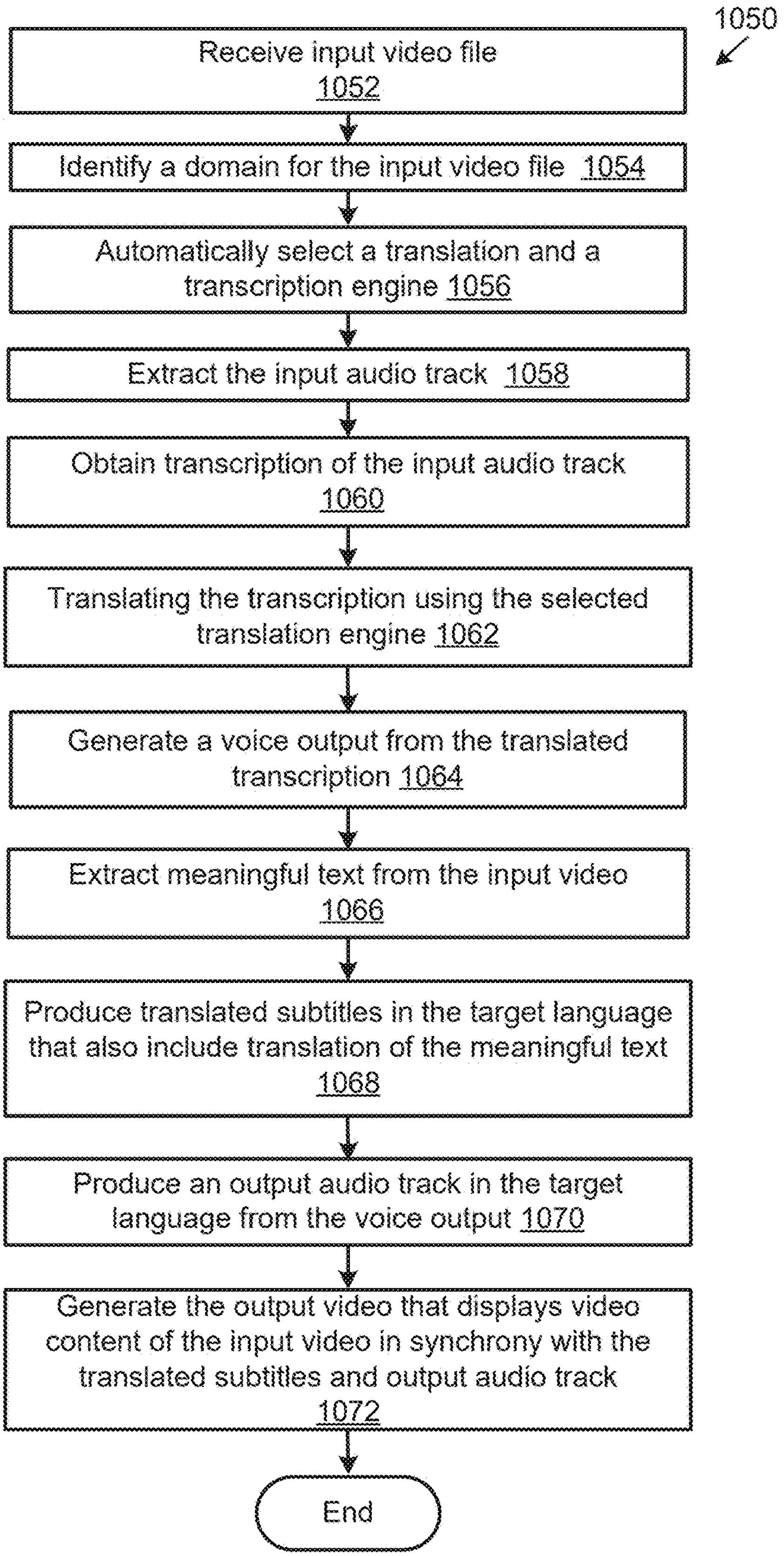

1050
Receive input video file
1052
Identify a domain for the input video file 1054
Automatically select a translation and a transcription engine 1056
Extract the input audio track 1058
Obtain transcription of the input audio track
1060
Translating the transcription using the selected translation engine 1062
Generate a voice output from the translated transcription 1064
Extract meaningful text from the input video
1066
Produce translated subtitles in the target language that also include translation of the meaningful text
1068
Produce an output audio track in the target language from the voice output 1070
Generate the output video that displays video content of the input video in synchrony with the translated subtitles and output audio track
1072
End

FIG. 1B

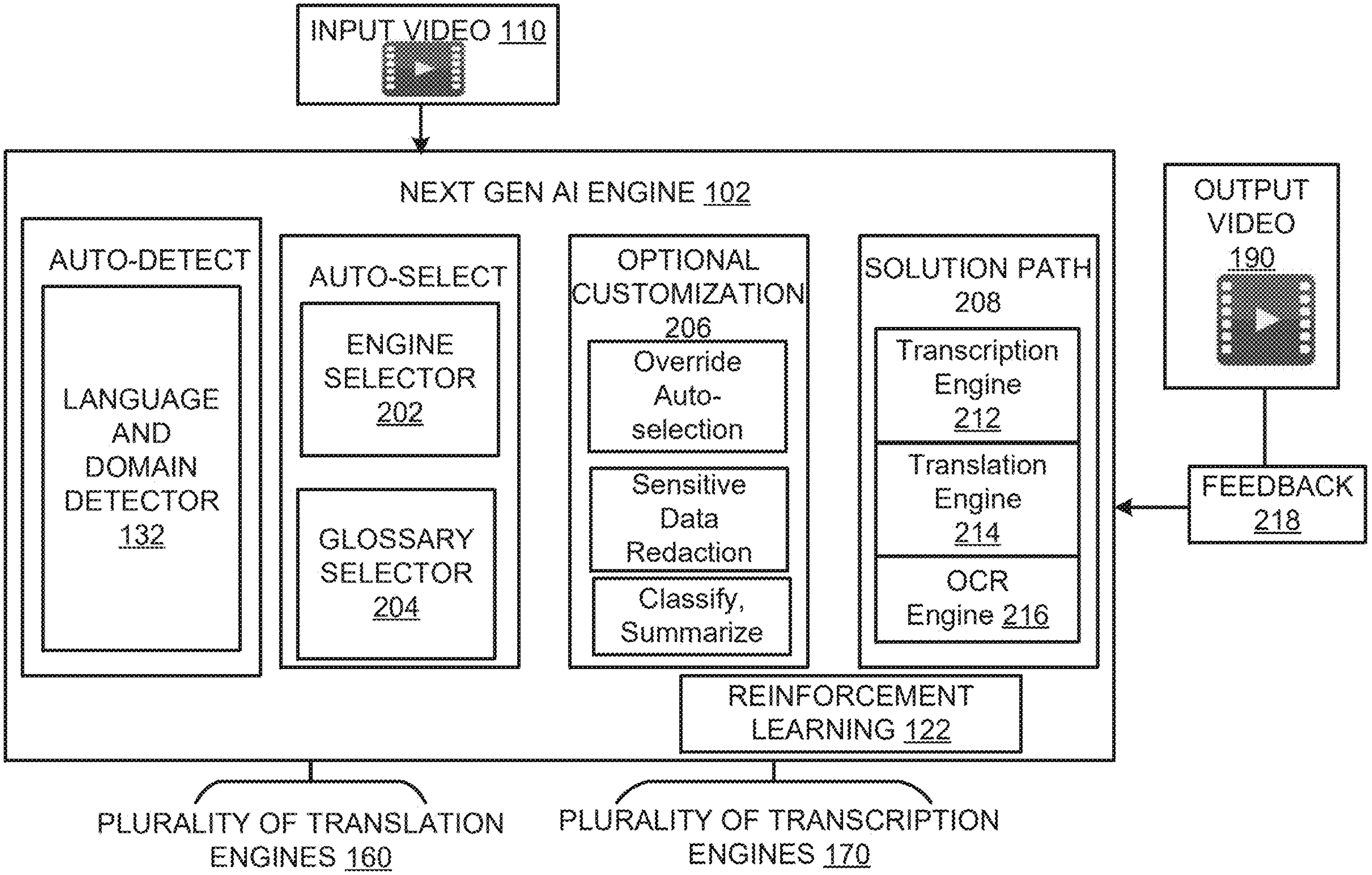

INPUT VIDEO 110
NEXT GEN AI ENGINE 102
AUTO-DETECT
LANGUAGE AND DOMAIN DETECTOR 132
AUTO-SELECT
ENGINE SELECTOR 202
GLOSSARY SELECTOR 204
OPTIONAL CUSTOMIZATION 206
Override Auto-selection
Sensitive Data Redaction
Classify, Summarize
SOLUTION PATH 208
Transcription Engine 212
Translation Engine 214
OCR Engine 216
REINFORCEMENT LEARNING 122
OUTPUT VIDEO 190
FEEDBACK 218
PLURALITY OF TRANSLATION ENGINES 160
PLURALITY OF TRANSCRIPTION ENGINES 170

FIG. 2A

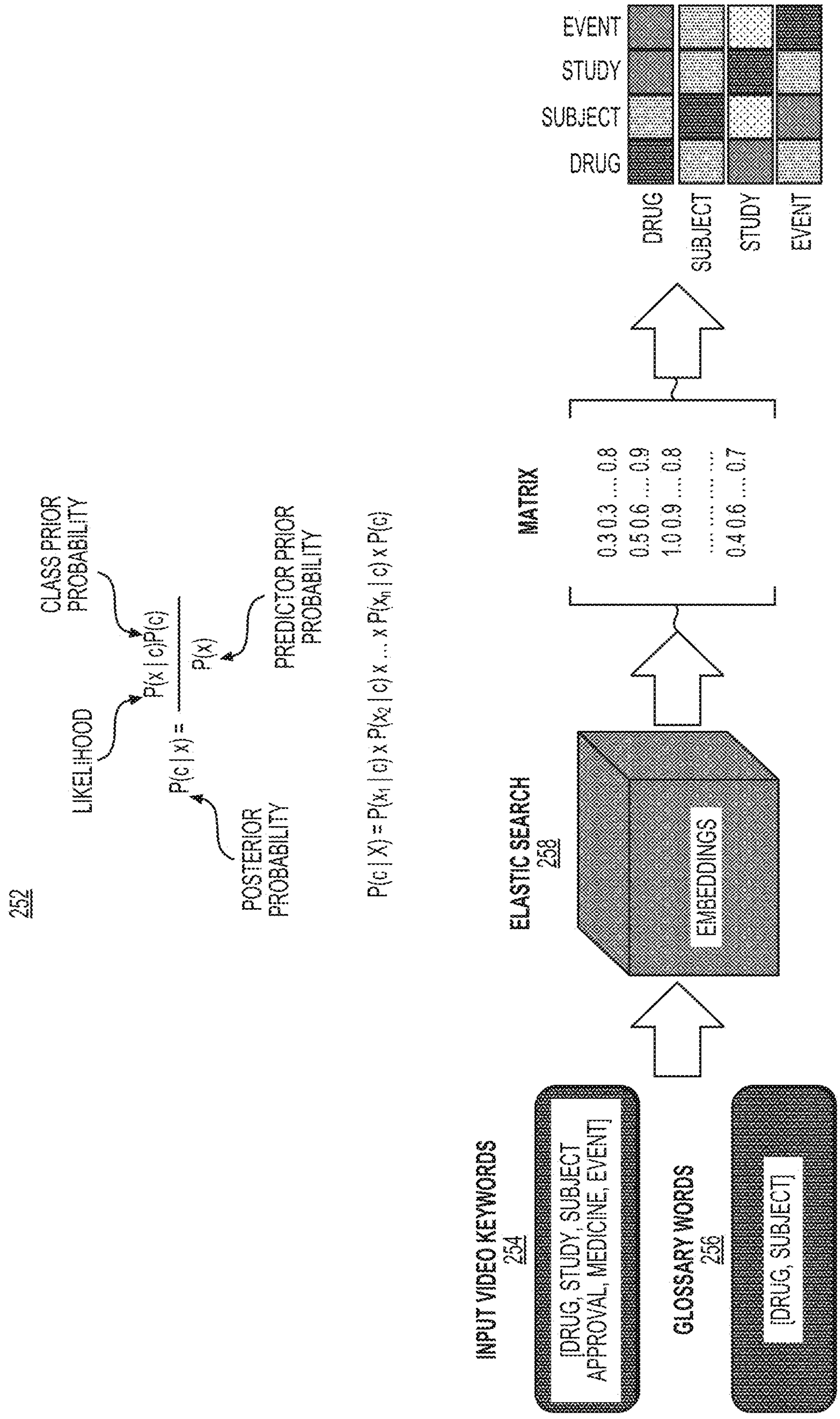

252
LIKELIHOOD
CLASS PRIOR PROBABILITY
$P(c \mid x) = \frac{P(x \mid c)P(c)}{P(x)}$
POSTERIOR PROBABILITY
PREDICTOR PRIOR PROBABILITY
$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \ldots \times P(x_n \mid c) \times P(c)$
INPUT VIDEO KEYWORDS
254
[DRUG, STUDY, SUBJECT APPROVAL, MEDICINE, EVENT]
GLOSSARY WORDS
256
[DRUG, SUBJECT]
ELASTIC SEARCH
258
EMBEDDINGS
MATRIX
0.3 0.3 .... 0.8
0.5 0.6 .... 0.9
1.0 0.9 .... 0.8
.... .... ....
0.4 0.6 .... 0.7
DRUG
SUBJECT
STUDY
EVENT
DRUG
SUBJECT
STUDY
EVENT

FIG. 2B

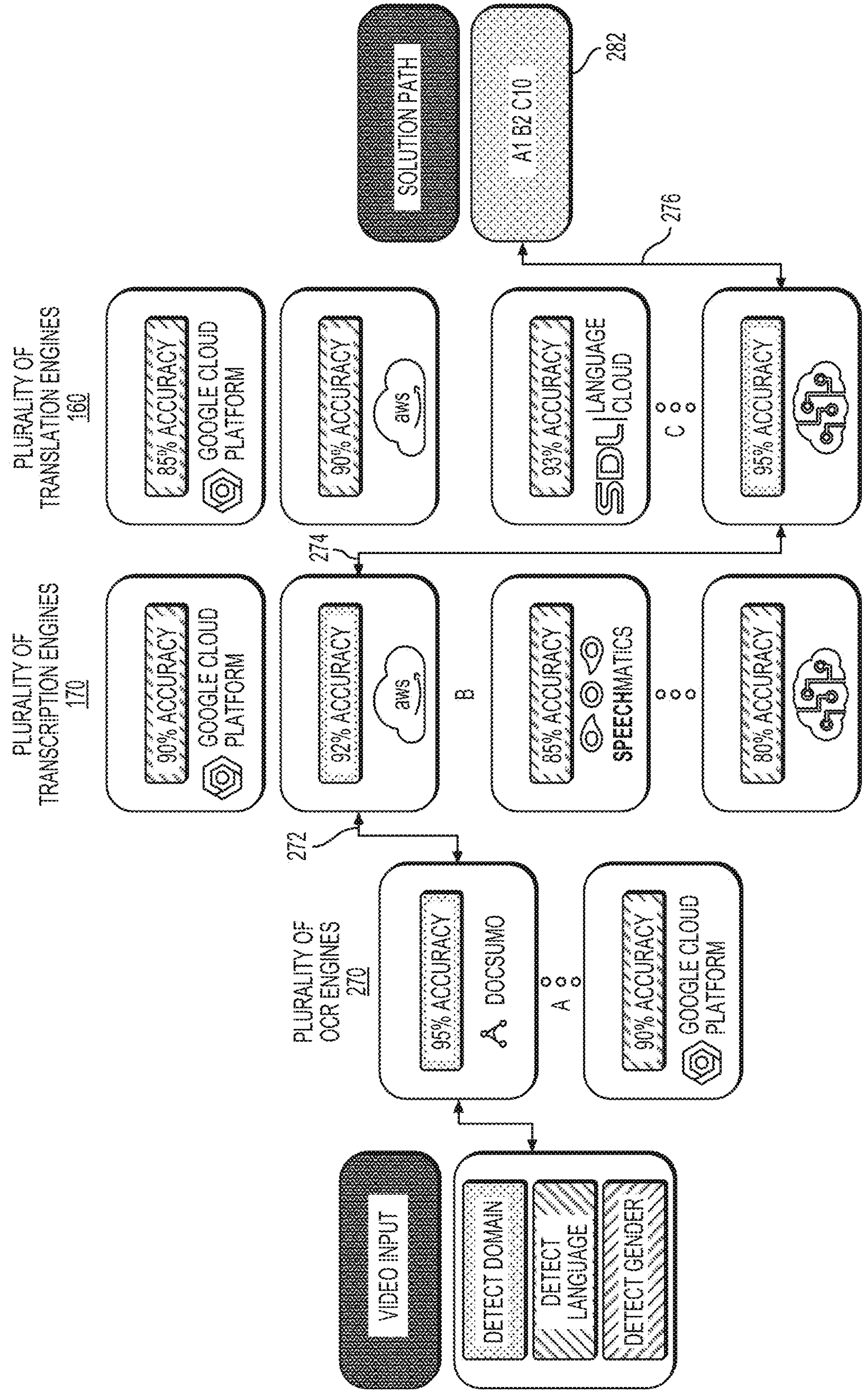

VIDEO INPUT
DETECT DOMAIN
DETECT LANGUAGE
DETECT GENDER
PLURALITY OF OCR ENGINES 270
95% ACCURACY
DOCSUMO
A
90% ACCURACY
GOOGLE CLOUD PLATFORM
272
PLURALITY OF TRANSCRIPTION ENGINES 170
90% ACCURACY
GOOGLE CLOUD PLATFORM
92% ACCURACY
aws
B
85% ACCURACY
SPEECHMATICS
80% ACCURACY
274
PLURALITY OF TRANSLATION ENGINES 160
85% ACCURACY
GOOGLE CLOUD PLATFORM
90% ACCURACY
aws
93% ACCURACY
SDL LANGUAGE CLOUD
C
95% ACCURACY
276
SOLUTION PATH
A1 B2 C10
282

FIG. 2C

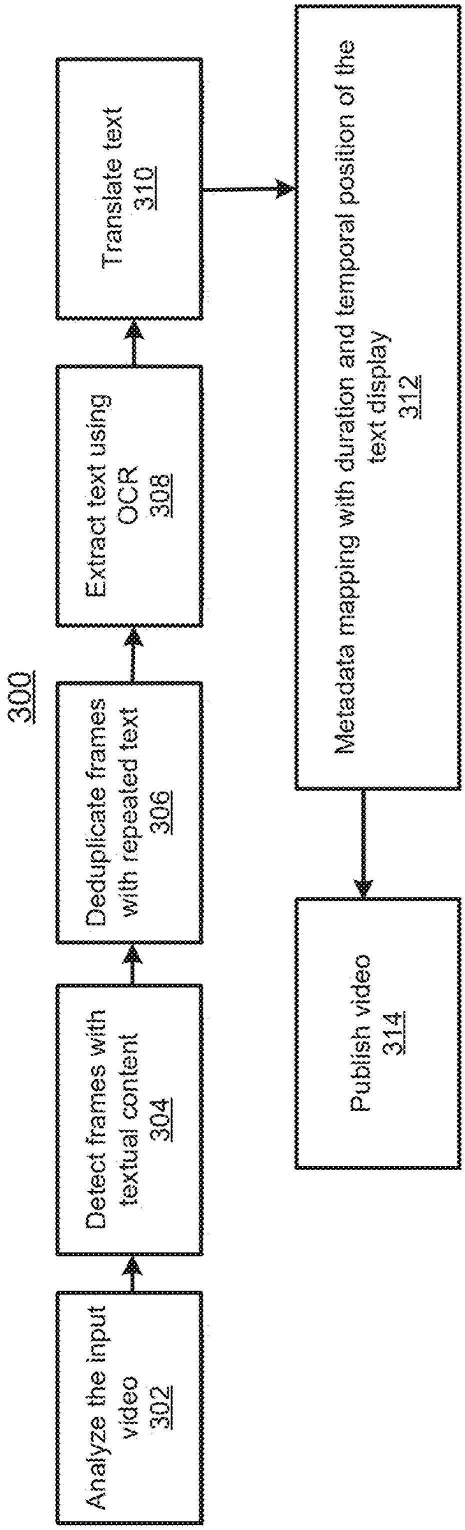

300
Analyze the input video 302
Detect frames with textual content 304
Deduplicate frames with repeated text 306
Extract text using OCR 308
Translate text 310
Metadata mapping with duration and temporal position of the text display 312
Publish video 314

FIG. 3A

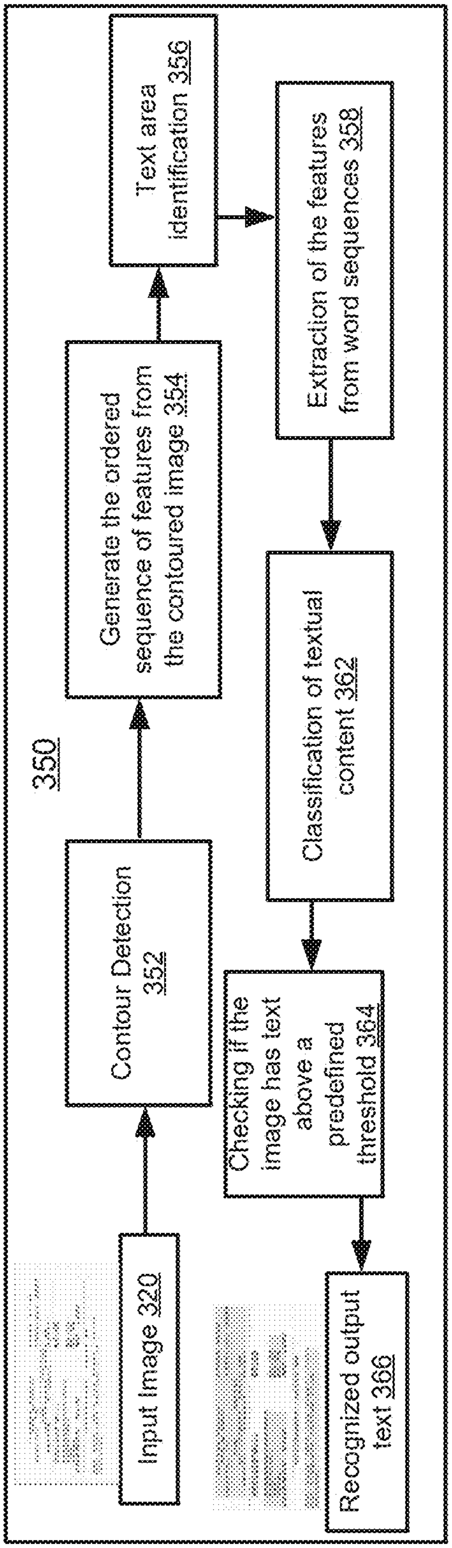

350
Input Image 320
Contour Detection 352
Generate the ordered sequence of features from the contoured image 354
Text area identification 356
Extraction of the features from word sequences 358
Classification of textual content 362
Checking if the image has text above a predefined threshold 364
Recognized output text 366

FIG. 3B

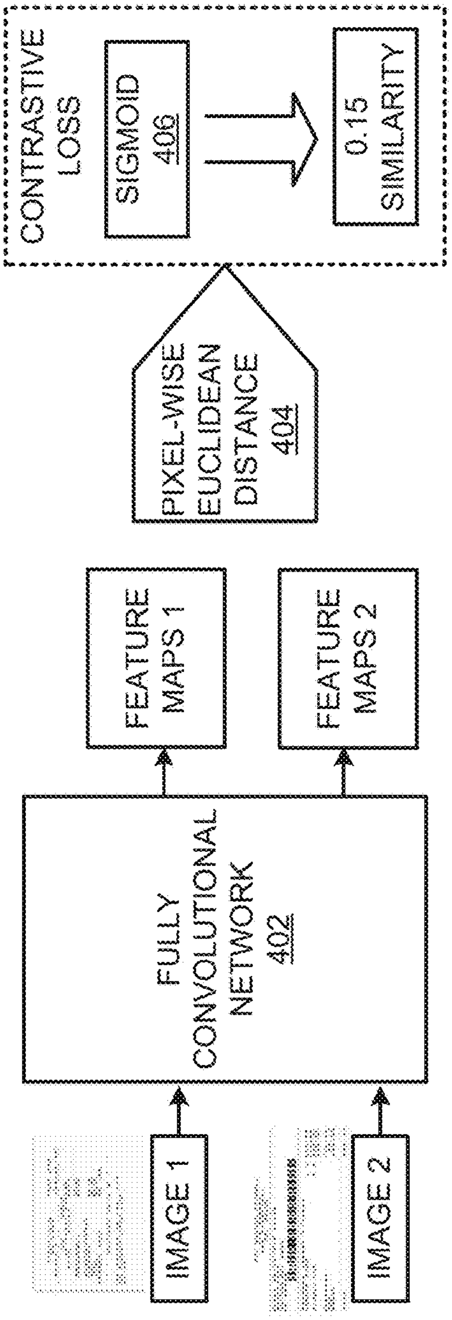


IMAGE 1
IMAGE 2
FULLY CONVOLUTIONAL NETWORK 402
FEATURE MAPS 1
FEATURE MAPS 2
PIXEL-WISE EUCLIDEAN DISTANCE 404
CONTRASTIVE LOSS
SIGMOID 406
0.15 SIMILARITY

FIG. 4A

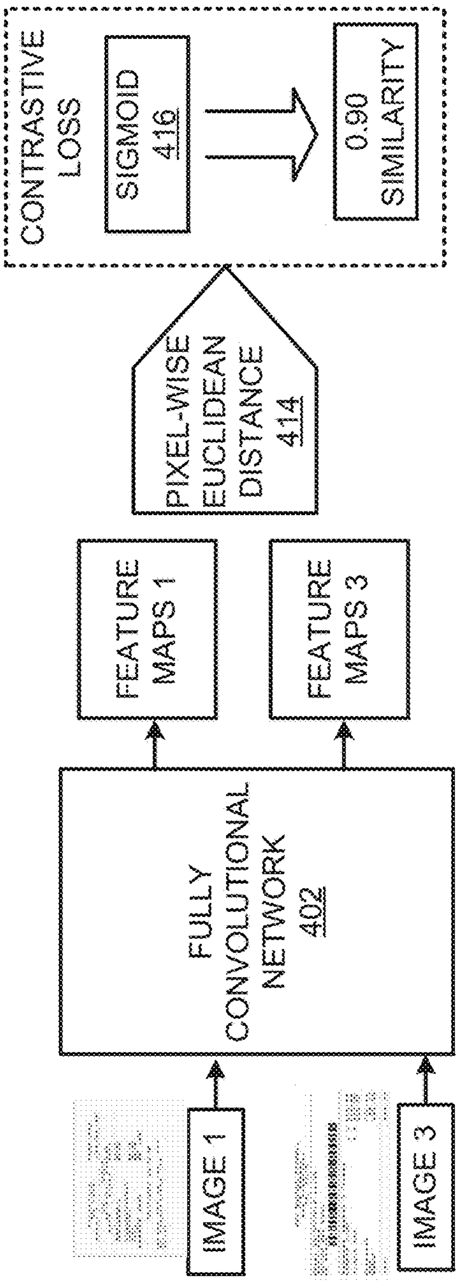


IMAGE 1
IMAGE 3
FULLY CONVOLUTIONAL NETWORK 402
FEATURE MAPS 1
FEATURE MAPS 3
PIXEL-WISE EUCLIDEAN DISTANCE 414
CONTRASTIVE LOSS
SIGMOID 416
0.90 SIMILARITY

FIG. 4B

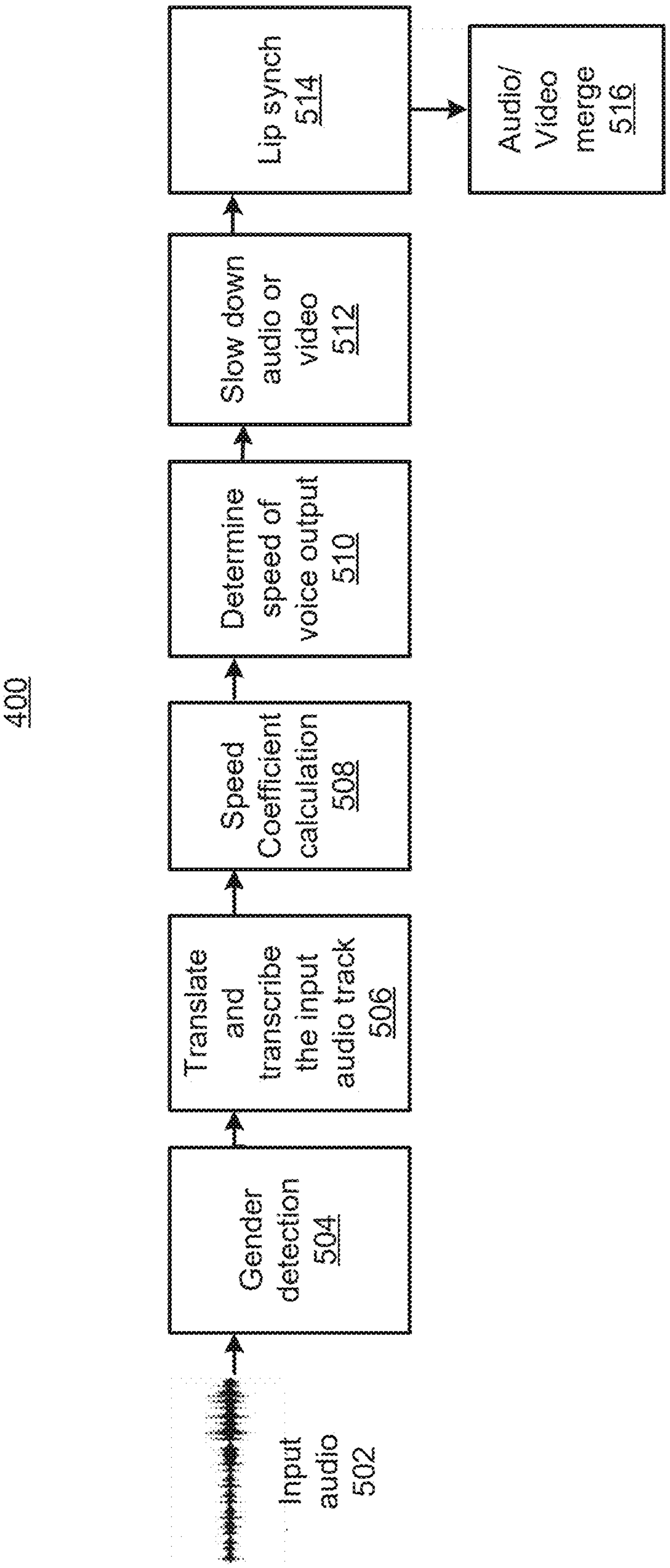

400
Input audio 502
Gender detection 504
Translate and transcribe the input audio track 506
Speed Coefficient calculation 508
Determine speed of voice output 510
Slow down audio or video 512
Lip synch 514
Audio/ Video merge 516

FIG. 5

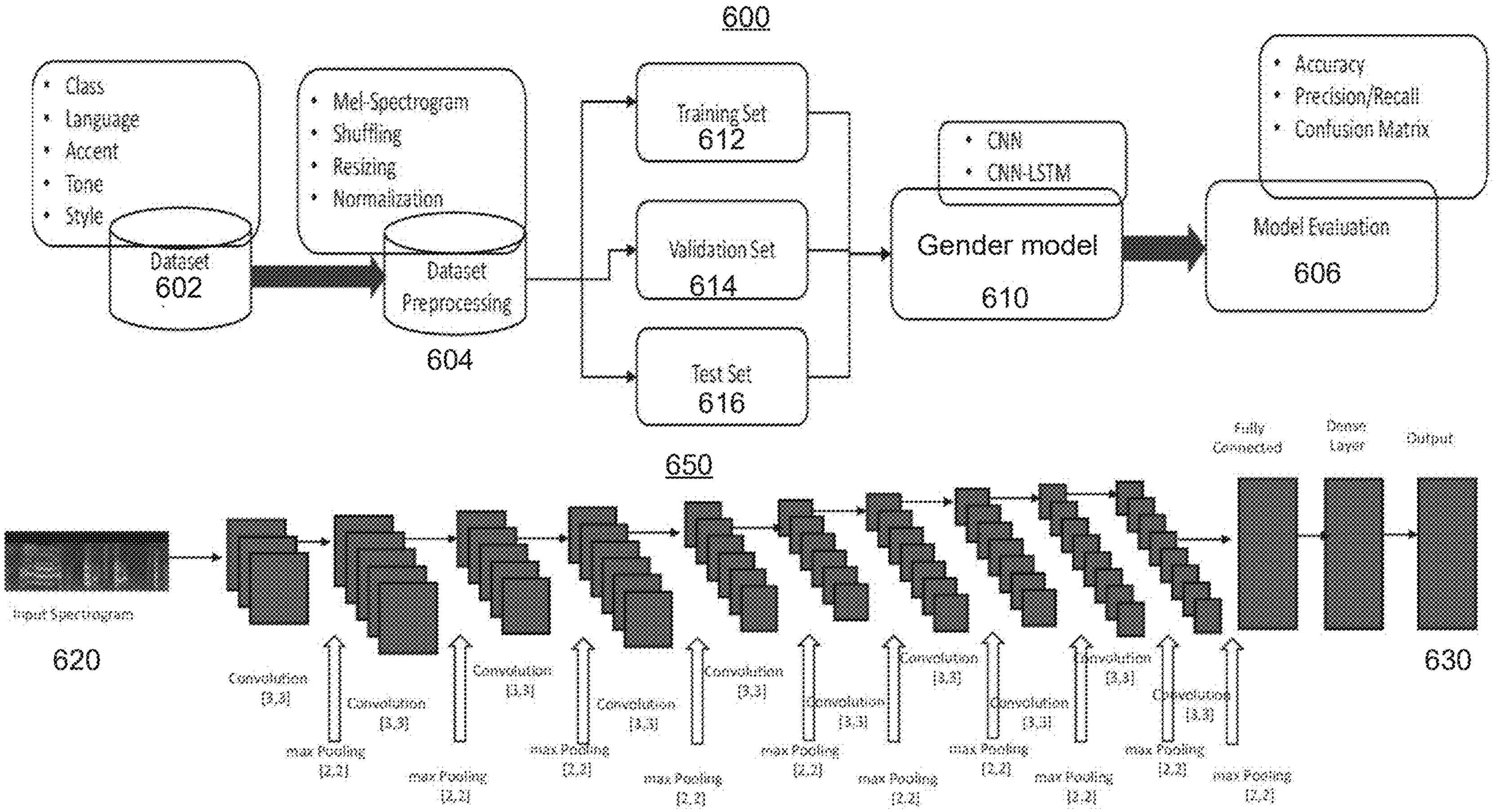

600
• Class
• Language
• Accent
• Tone
• Style
Dataset
602
• Mel-Spectrogram
• Shuffling
• Resizing
• Normalization
Dataset
Preprocessing
604
Training Set
612
Validation Set
614
Test Set
616
• CNN
• CNN-LSTM
Gender model
610
• Accuracy
• Precision/Recall
• Confusion Matrix
Model Evaluation
606
650
Input Spectrogram
620
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Convolution
[3,3]
max Pooling
[2,2]
Fully
Connected
Dense
Layer
Output
630

FIG. 6

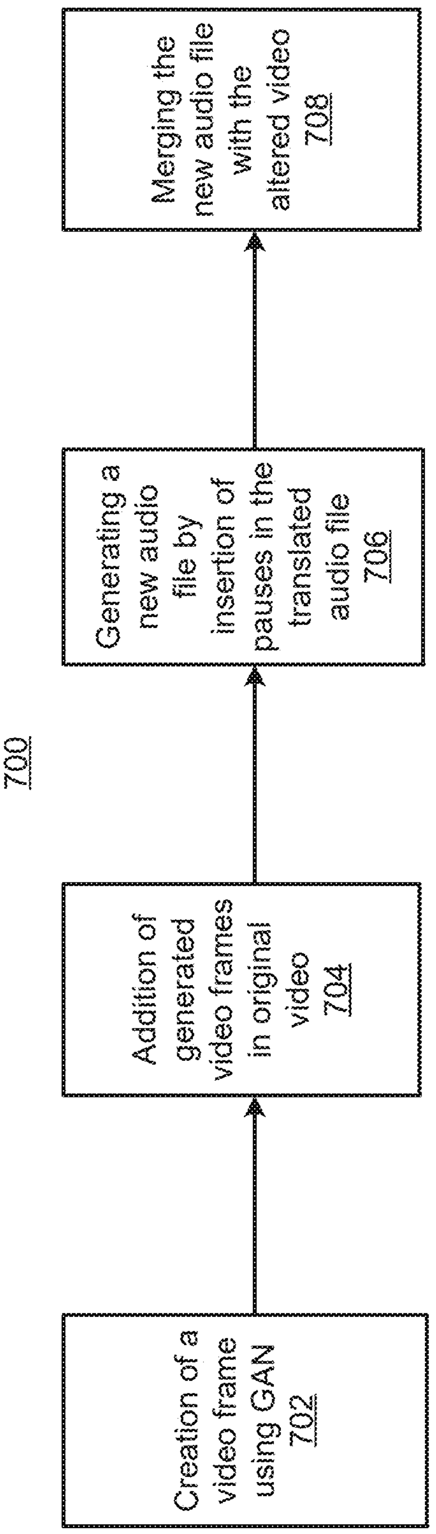

700
Creation of a video frame using GAN 702
Addition of generated video frames in original video 704
Generating a new audio file by insertion of pauses in the translated audio file 706
Merging the new audio file with the altered video 708

FIG. 7

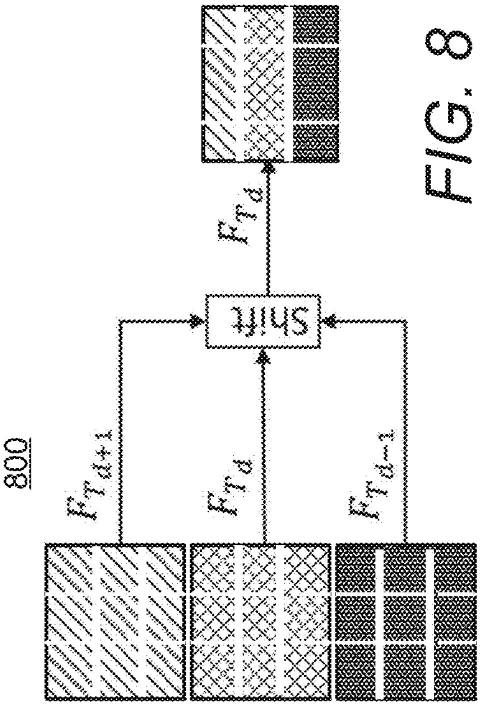

800
$F_{T_{d+1}}$
$F_{T_d}$
$F_{T_{d-1}}$
Shift
$F_{T_d}$

FIG. 8

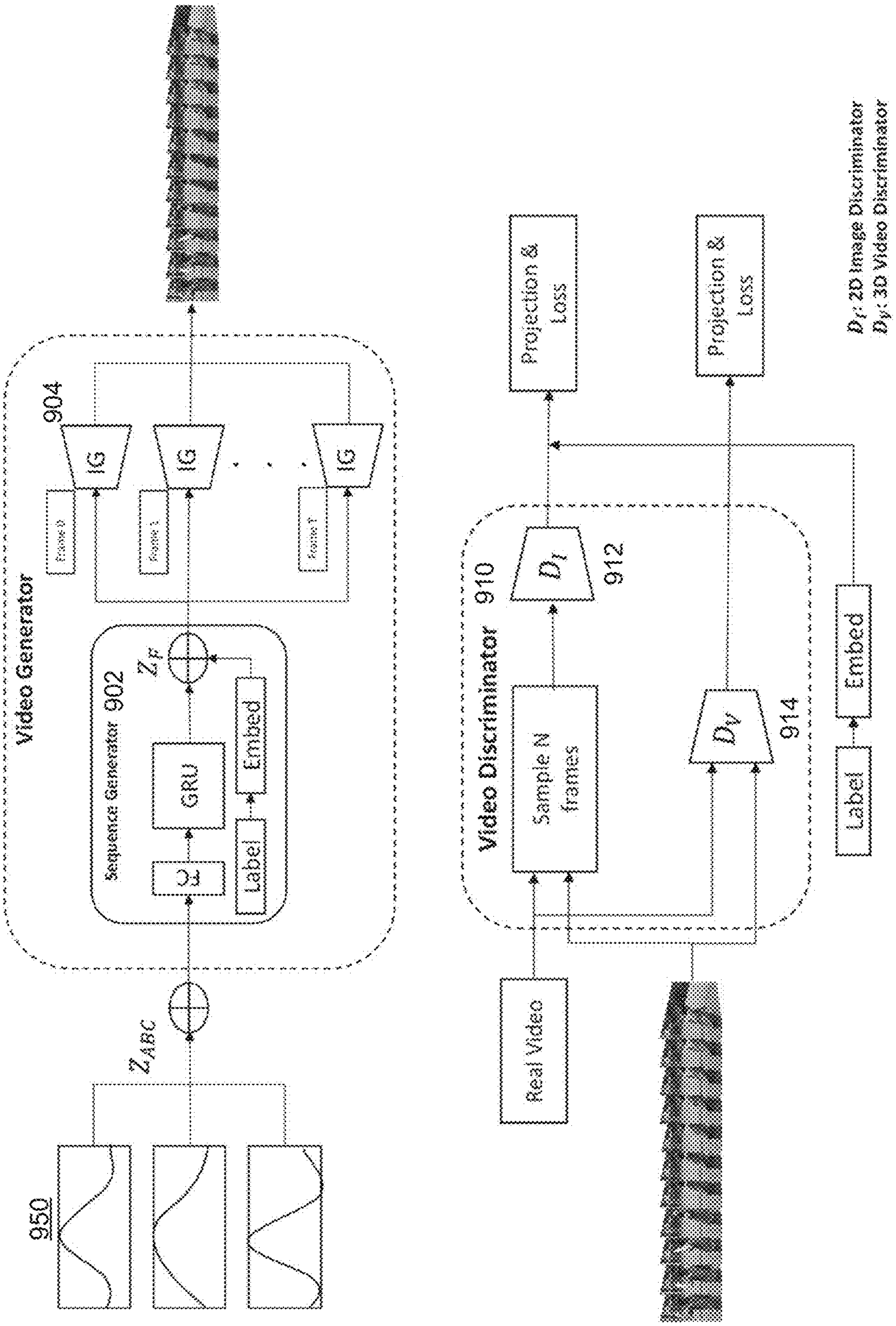

950
$Z_{ABC}$
900
Video Generator
Sequence Generator 902
FC
GRU
Label
Embed
$Z_F$
Frame 0
Frame 1
Frame T
IG
IG
IG
904
Video Discriminator 910
Sample N frames
$D_I$
912
$D_V$
914
Real Video
Label
Embed
Projection & Loss
Projection & Loss
$D_I$: 2D Image Discriminator
$D_V$: 3D Video Discriminator

FIG. 9

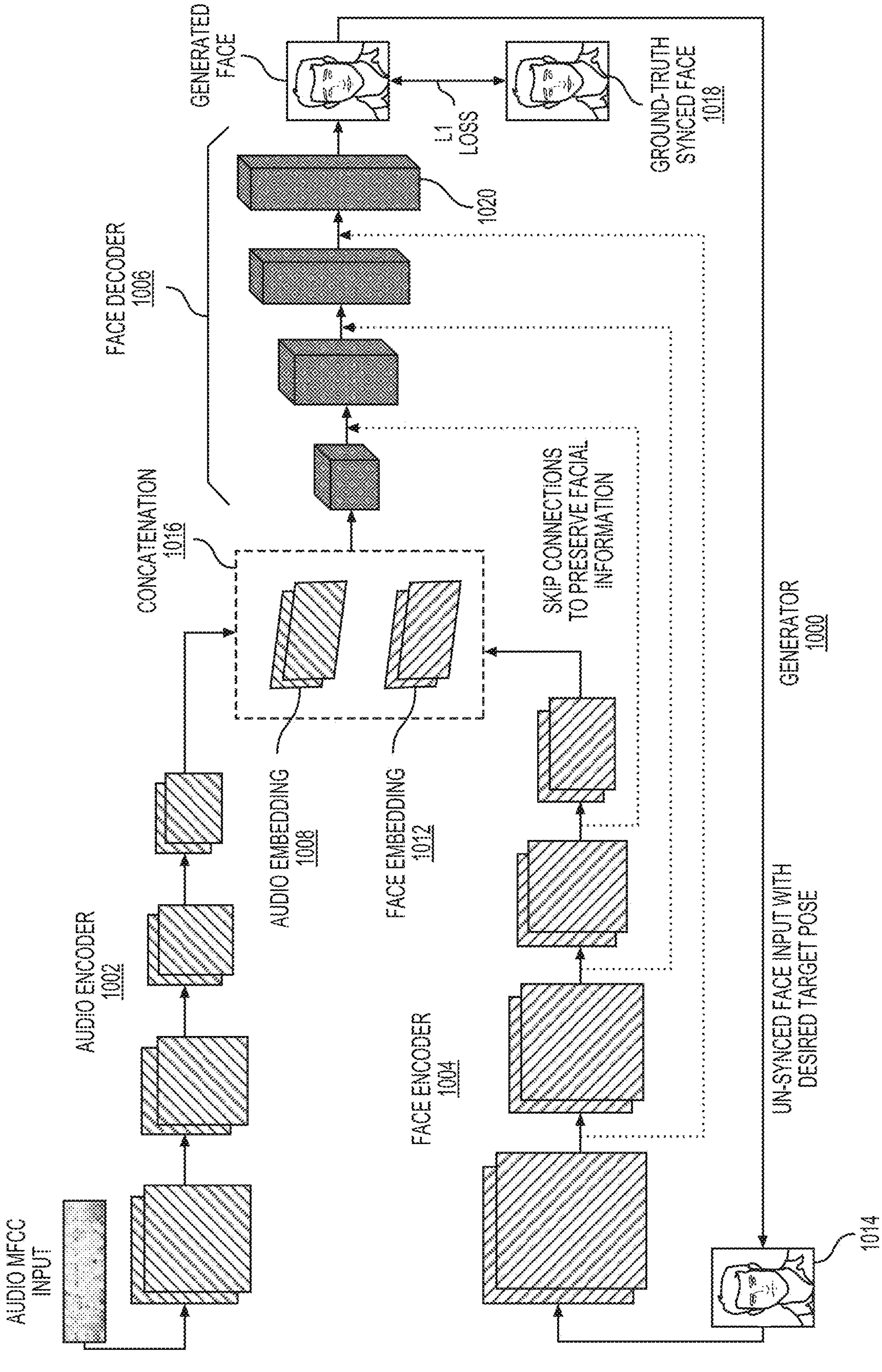

AUDIO MFCC INPUT
AUDIO ENCODER 1002
FACE ENCODER 1004
AUDIO EMBEDDING 1008
FACE EMBEDDING 1012
CONCATENATION 1016
SKIP CONNECTIONS TO PRESERVE FACIAL INFORMATION
FACE DECODER 1006
1020
GENERATED FACE
L1 LOSS
GROUND-TRUTH SYNCED FACE 1018
GENERATOR 1000
UN-SYNCED FACE INPUT WITH DESIRED TARGET POSE
1014

FIG. 10

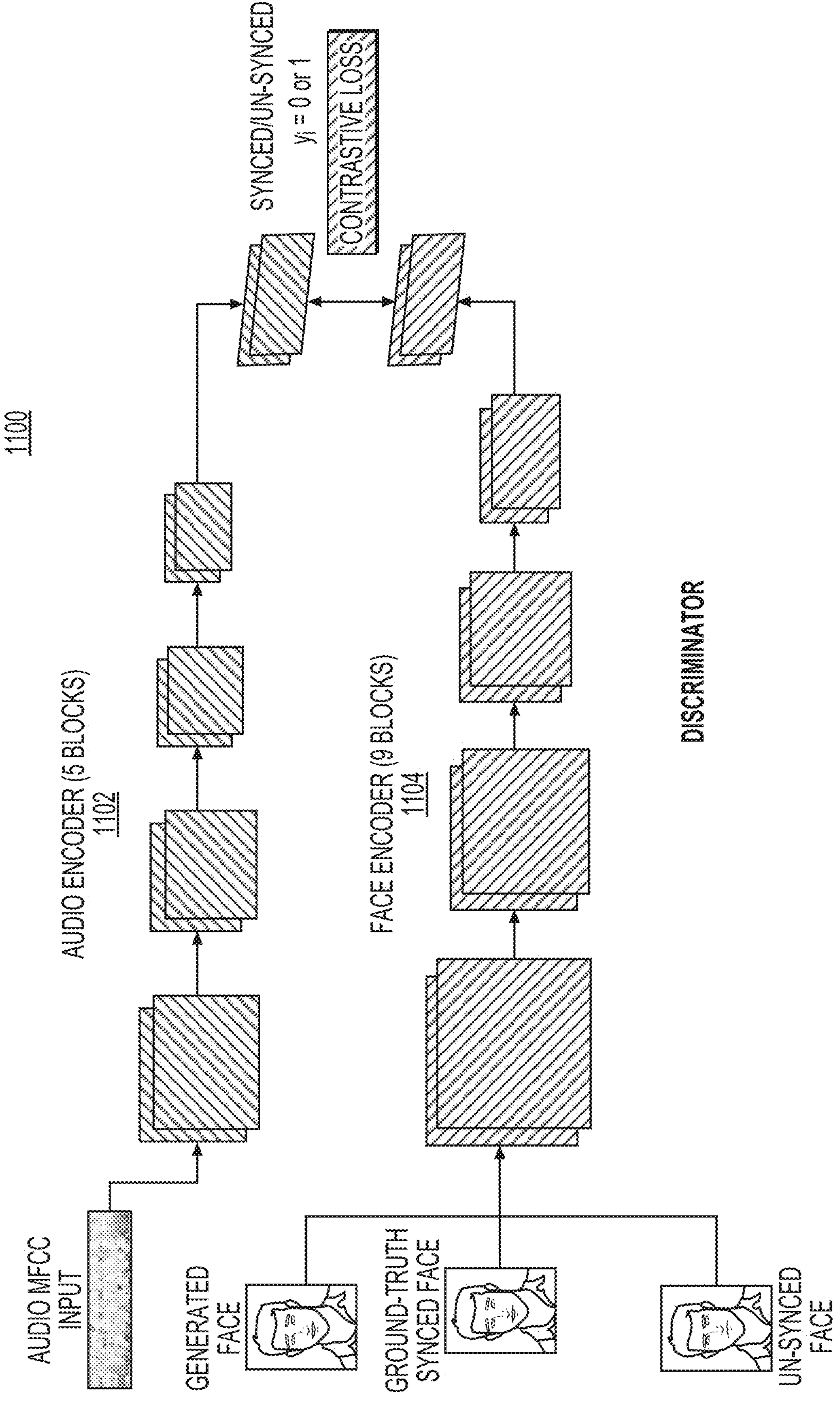

1100
AUDIO ENCODER (5 BLOCKS)
1102
FACE ENCODER (9 BLOCKS)
1104
AUDIO MFCC INPUT
GENERATED FACE
GROUND-TRUTH SYNCED FACE
UN-SYNCED FACE
SYNCED/UN-SYNCED?
$y_i$ = 0 or 1
CONTRASTIVE LOSS
DISCRIMINATOR

FIG. 11

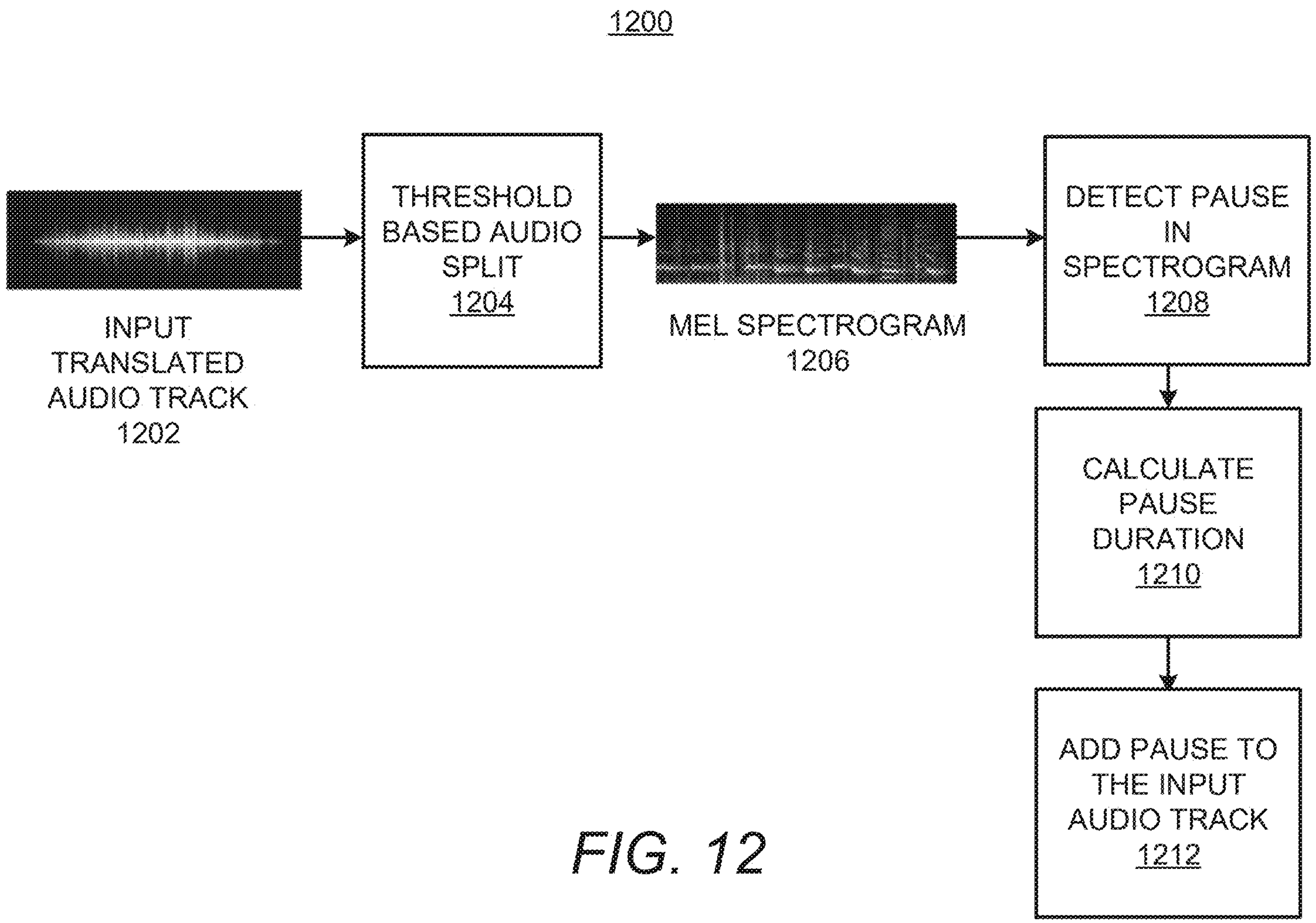

1200
INPUT TRANSLATED AUDIO TRACK 1202
THRESHOLD BASED AUDIO SPLIT 1204
MEL SPECTROGRAM 1206
DETECT PAUSE IN SPECTROGRAM 1208
CALCULATE PAUSE DURATION 1210
ADD PAUSE TO THE INPUT AUDIO TRACK 1212

FIG. 12

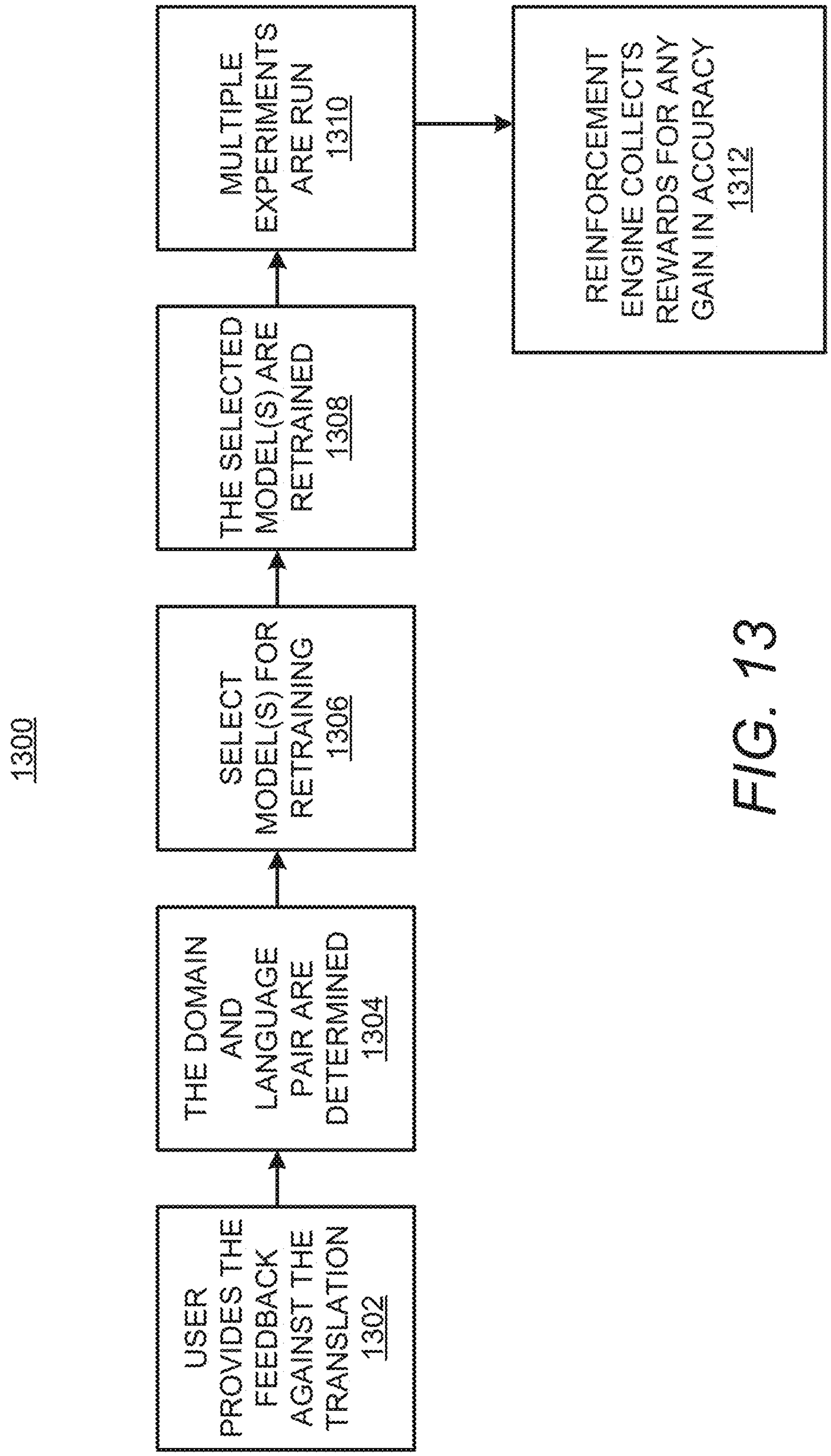

1300
USER PROVIDES THE FEEDBACK AGAINST THE TRANSLATION 1302
THE DOMAIN AND LANGUAGE PAIR ARE DETERMINED 1304
SELECT MODEL(S) FOR RETRAINING 1306
THE SELECTED MODEL(S) ARE RETRAINED 1308
MULTIPLE EXPERIMENTS ARE RUN 1310
REINFORCEMENT ENGINE COLLECTS REWARDS FOR ANY GAIN IN ACCURACY 1312

FIG. 13

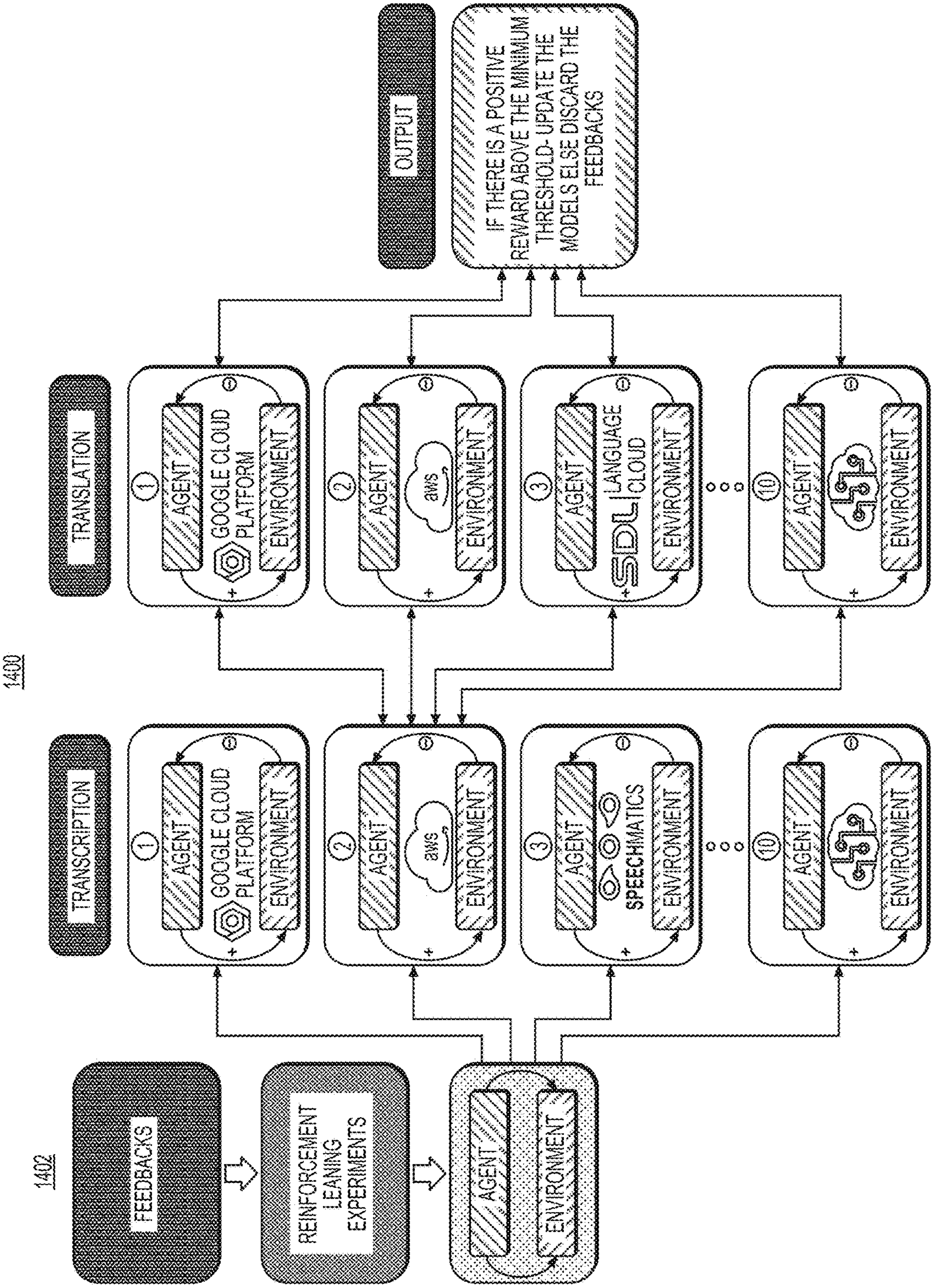

1400
1402
FEEDBACKS
REINFORCEMENT LEANING EXPERMENTS
AGENT
ENVIRONMENT
TRANSCRIPTION
1
AGENT
GOOGLE CLOUD PLATFORM
ENVIRONMENT
+
⊖
2
AGENT
aws
ENVIRONMENT
+
⊖
3
AGENT
SPEECHMATICS
ENVIRONMENT
+
⊖
10
AGENT
ENVIRONMENT
+
⊖
TRANSLATION
1
AGENT
GOOGLE CLOUD PLATFORM
ENVIRONMENT
+
⊖
2
AGENT
aws
ENVIRONMENT
+
⊖
3
AGENT
SDL LANGUAGE CLOUD
ENVIRONMENT
+
⊖
10
AGENT
ENVIRONMENT
+
⊖
OUTPUT
IF THERE IS A POSITIVE REWARD ABOVE THE MINIMUM THRESHOLD- UPDATE THE MODELS ELSE DISCARD THE FEEDBACKS

FIG. 14

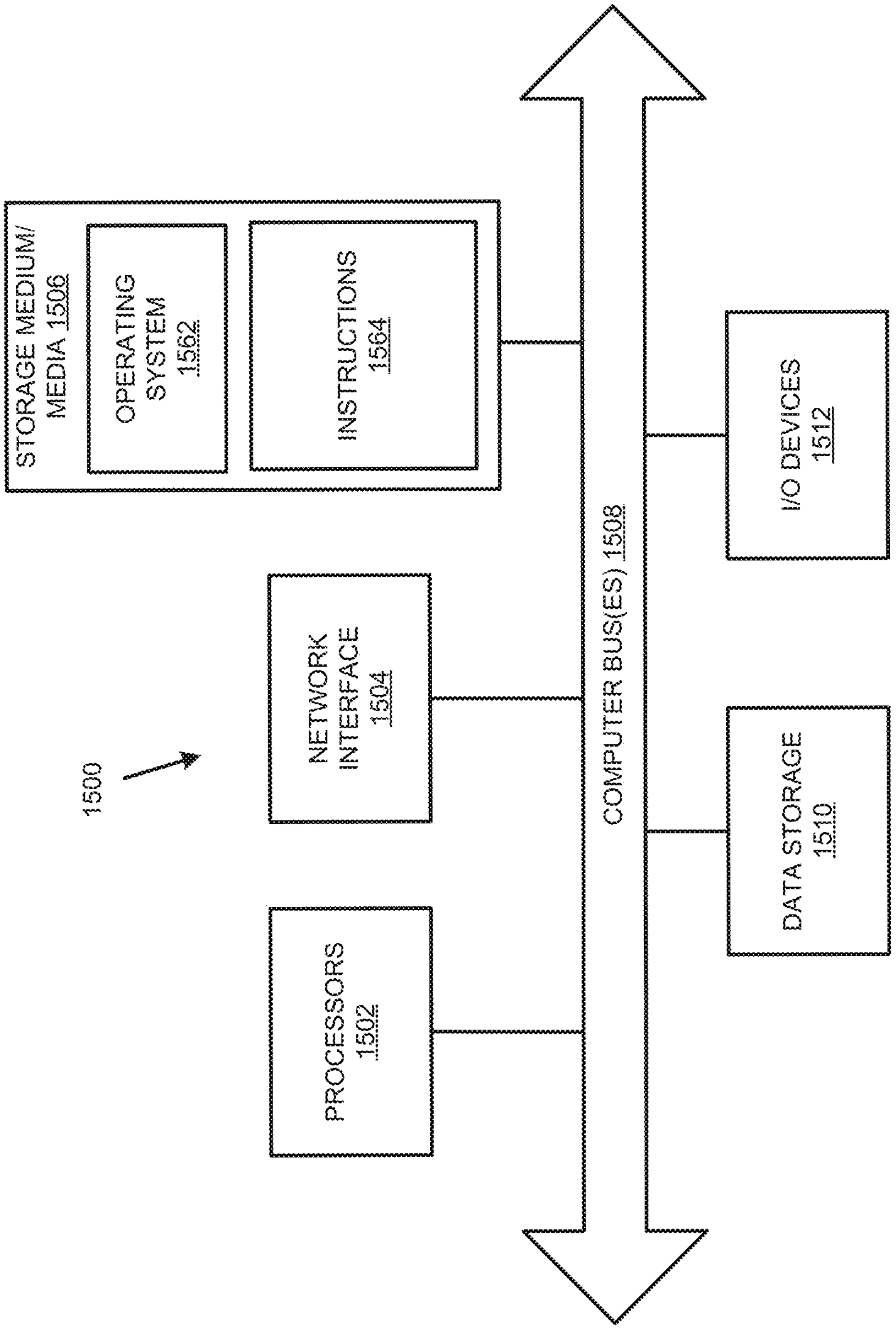

1500
PROCESSORS
1502
NETWORK
INTERFACE
1504
STORAGE MEDIUM/
MEDIA 1506
OPERATING
SYSTEM
1562
INSTRUCTIONS
1564
COMPUTER BUS(ES) 1508
DATA STORAGE
1510
I/O DEVICES
1512

FIG. 15

# VIDEO TRANSLATION PLATFORM

## PRIORITY

The present non-provisional application claims priority to the Indian Provisional Patent Application Serial No. 202211021128, having a filing date of Apr. 8, 2022, and the Indian Provisional Patent Application Serial No. 202211023590, having a filing date of Apr. 21, 2022, the disclosures of which are hereby incorporated by reference in their entireties.

## BACKGROUND

Computers have long been used for translating text from one language to another. Automatic or machine translation is one of the important functions enabled by artificial intelligence (AI) technologies. Classically, rule-based systems were used for this task. However, these systems were later replaced with systems using statistical methods. More recently, deep neural network (DNN) models achieve state-of-the-art results in the field of neural machine translation.

## BRIEF DESCRIPTION OF DRAWINGS

Features of the present disclosure are illustrated by way of examples shown in the following figures. In the following figures, like numerals indicate like elements, in which:

FIG. **1**A shows a block diagram of a video translation system in accordance with the examples disclosed herein.

FIG. **1**B shows a flowchart that shows a method of translating the input video into a target language in accordance with the examples disclosed herein.

FIG. **2**A shows a block diagram of a NextGen AI engine in accordance with the examples disclosed herein.

FIG. **2**B shows some custom models employed in the NextGen AI engine in accordance with the examples disclosed herein.

FIG. **2**C shows a block diagram of the generation of a solution path by the NextGen AI engine in accordance with the examples disclosed herein.

FIG. **3**A shows a block diagram of the various steps involved in extracting text from an input video in accordance with the examples disclosed herein.

FIG. **3**B shows a block diagram of the steps of identifying text from a given frame in accordance with the examples disclosed herein.

FIGS. **4**A and **4**B illustrate the duplication of video frames in accordance with the examples disclosed herein.

FIG. **5** shows a block diagram of the steps involved in an audio dubbing process in accordance with the examples disclosed herein.

FIG. **6** shows an architecture for gender detection for audio dubbing in accordance with the examples disclosed herein.

FIG. **7** shows a block diagram of the various steps involved in automatic video frame generation in accordance with the examples disclosed herein.

FIG. **8** shows a diagram of a temporal shift in accordance with the examples disclosed herein.

FIG. **9** shows the architecture of a video generator in accordance with the examples disclosed herein.

FIG. **10** shows a generator architecture for lip-synching using a Generative Adversarial Network (GAN) in accordance with the examples disclosed herein.

FIG. **11** shows a discriminator architecture for lip-synching using GAN in accordance with the examples disclosed herein.

FIG. **12** shows the steps involved in generating the translated subtitles in accordance with the examples disclosed herein.

FIG. **13** shows the steps for automatic feedback incorporation using reinforcement learning in accordance with the examples disclosed herein.

FIG. **14** shows the incorporation of reinforcement learning for retraining the NextGen Ai engine in accordance with the examples disclosed herein.

FIG. **15** illustrates a computer system that may be used to implement the video translation system in accordance with the examples disclosed herein.

## DETAILED DESCRIPTION

For simplicity and illustrative purposes, the present disclosure is described by referring to examples thereof. In the following description, numerous specific details are set forth in order to provide a thorough understanding of the present disclosure. It will be readily apparent however that the present disclosure may be practiced without limitation to these specific details. In other instances, some methods and structures have not been described in detail so as not to unnecessarily obscure the present disclosure. Throughout the present disclosure, the terms “a” and “an” are intended to denote at least one of a particular element. As used herein, the term “includes” means includes but not limited to, the term “including” means including but not limited to. The term “based on” means based at least in part on.

A video translation system that generates an output video corresponding to a translated version of a received input video is disclosed. The input video may be received along with a selection of a target language into which it is to be translated. In an example, the input video may include an audio track in an input language/source language while the output video may be generated in an output language/target language. When the input video is received, a NextGen AI engine identifies a domain of the input video. Based at least on the domain, the source language, and target language, the NextGen AI engine can recommend a solution path that may include the best translation engine, transcription engine, and an Optical Character Recognition (OCR) engine for the identified domain and the source/target language pair that can provide the highest translation accuracy. The translation engine and the transcription engine can be selected so that they provide the highest accuracy for the translation/transcription tasks from amongst the available options.

The input audio track is extracted from the input video and used for gender detection wherein the gender of the different voices speaking in the input audio track are identified by gender detection models. In an example, if the input audio track includes different voices of the same gender, then such differentiation may also be identified by the gender detection models. In addition, the pauses and the stop words occurring in the extracted input audio track are also identified. The meaningful text which may be present in different frames of the input video may also be extracted. Further, the selected transcription engine transcribes the input audio track to produce the transcribed text of the audio input. The transcribed text and the text extracted from the frames of the input video can be provided to the translation engine to obtain textual output translated into the target language. This textual output can be converted to speech to produce a voice output in the target language. In an example, the audio signals of the voice output may be divided into homogenous zones of speech that make up voice segments which can be further processed to generate an output audio track.

A speed coefficient is calculated for the voice output and one or more of the voice output and the input video may be manipulated or transformed if needed using different methods described herein so that they are in synchrony. In an example, pauses can be inserted into the voice output to generate an output audio track. In an example, the voice output may be used unmodified as the output audio track. In an example, the video content of the input video can be modified via the insertion of new video frames that are automatically generated using Generative Adversarial Networks (GANs). The images of speakers in the input video can also be modified so that the lip movements of the speakers in the images are synchronous with the output video track. The output video is generated by merging the output audio track with the modified video content. User feedback can be collected and automatically incorporated via reinforcement learning, to improve the machine learning (ML) models used for the domain identification, the translation, and the transcription engine selections.

The server-less, real-time, online video translation solution disclosed herein includes an interactive user interface to translate video content at the click of a button. The video translation system uses automation and Artificial Intelligence (AI) to transcribe a video and then translate the input audio track in the source language to the target language in order to make it suitable for multilingual audiences. The translated script generated from the transcribed input audio track can then be converted back to a translated audio and embedded with the video content to generate the output video. The video translation is enabled by features such as but not limited to custom/domain-specific glossaries, expert reviews, extraction of in-video content, a smart nextgen AI, auto-learning based on feedback from experts, and a security layer for protecting content and distribution. In an example, the video translation system can be made available as a Software as a Service (SaaS) solution to benefit from, at scale and pay-per-use. The video translation system described herein is available for translation 24×7 and delivers translation at high speed and very low cost as the majority of the translation/transcription work is automated.

FIG. **1** shows a diagram of a video translation system **100** in accordance with the examples disclosed herein. An input video **110** is received by the video translation system **100** which translates the audio and the textual content in the input video **110** to an output/target language and generates an output video **190**. In an example, the input video **110** can include an input audio track and/or textual content in one or more input/source languages. The output video **190**, would therefore include one or more of an output audio track in the target language and textual content translated from the source language into the target language. In an example, the translated textual content can be provided as subtitles in the output video **190**. Furthermore, the output video **190**, would also include video content manipulated or altered to suit the target language. In an example, the choice for the target languages can be provided with the input video **110** via a user interface. The input video **110** may be associated with a domain selected from a plurality of domains such as but not limited to healthcare, finance, education, management, scientific topics, entertainment content, etc.

When the input video **110** is received, the NextGen AI engine **102** activates the language and domain detector **132** to detect the source language and the domain associated with the input video **110**. Based at least on the source language/target language combination and the domain associated with the input video **110**, the best solution path selector **134** of the NextGen AI engine **102** can provide recommendation for the best solution path that includes a unique combination of a translation engine selected from a plurality of translation engines **160** and a transcription engine selected from a plurality of transcription engines **170** for carrying out the automated translation and transcription tasks. The selection of the translation engine can be based on the accuracy of the translation engine for the translation of the particular source/target language pair and the domain associated with the input video **110**. Similarly, the transcription service may also be selected based on the accuracies of the plurality of transcription engines **170** for the particular source language and the domain associated with the input video **110**. In an example, the NextGen AI engine **102** may provide an option that allows users to override the automatic selections of the translation and transcription engines to manually select the transcription/translation engines.

Upon identifying the optimal translation and transcription engines to be employed for the generation of the output video **190**, the input audio track is extracted by the audio extractor **104**. The input audio track may be stored as an audio file in formats such as .mp3, wav, etc. The audio extractor **104** can further include or be coupled to a gender detector **142**, a pause detector **144**, and a stop word identifier **146**. The gender detector **142** identifies different portions of the input audio track in the input video **110** as being spoken by different speakers. The gender detector **142** enables producing the translated audio output in the appropriate machine-generated voice. The pause detector **144** identifies pauses in the input audio track. Identification of pauses in the input video **110** enables accurately synchronizing the appearance of translated subtitles with the corresponding audio in the output video **190**. The stop word identifier **146**, further identifies different stop words occurring in the audio input of the input video **110**. Different languages may have different stop words and identification of such stop words, enables breaking off the subtitles in synchrony with the audio component of the output video **190**, so that meaningful subtitles can be displayed.

The input video **110** is then processed for text extraction by the text extractor **106**. In an example, the input video **110** can include certain portions with textual content in the source language which may be important for a viewer to understand in order to follow the proceedings of the input video **110**. The text extractor **106** from the input video **110** may involve analyzing the frames of the input video **110** to identify those frames with meaningful textual content. Optical character recognition (OCR), may then be applied to those frames for text extraction. Automatic identification of the frames with meaningful textual content can involve certain thresholds such as the extent of textual content in a given frame so that processing resources are not wasted in translating or transcribing irrelevant content. The selected transcription service is employed by a voice-to-text converter **108** for generating textual form or a transcription of the input audio track extracted from the input video **110**. The transcription from the voice-to-text converter **108** may be provided in the source language to the text translator **112** which translates the transcription to the target language using the translation service selected by the NextGen AI engine **102**. In an example, the textual inputs to the textual translator **112** may also include the source language textual output/meaningful text obtained from the selected frames by the text extractor **106**. The text translator **112**, therefore, produces translated textual content in the target language not only for the input audio track but also for the meaningful textual content identified and extracted from the input video frames. The text-to-speech converter **114** produces a voice output in the target language corresponding to the translated textual content obtained from the textual translator **112**. The voice output can include multiple voice segments or portions that may pertain to different speakers who may or may not be of different genders associated with the different portions. Accordingly, the voice output can be produced automatically in the corresponding gender by the audio dubbing **116** using voice-to-text synthesizers executed by an output file processor **136**. In an example, the text-to-speech converter **114** uses the output from the gender detector **142** for audio dubbing **116** to generate a gender-specific output audio track in the target language. In an example, even if different speakers are identified as the same gender, different voices/tones may be used for their voice segments. The output file processor **136** alters or manipulates the video content of the input video **110** to be synchronous with the output audio track. The one or more segments of the audio track are embedded **118** with the altered video content to generate the output video **190**.

The video translation system **100** includes an automatic feedback facilitator **120** for improving the various AI models used throughout the translation pipeline. Feedback given by users and language experts can be automatically incorporated using reinforcement learning **122**. In an example, feedback may be automatically incorporated via model retraining **124** and glossary updates. Based at least on certain model efficiency thresholds, it may be determined by the model publisher **126** whether the retrained models should be published to the translation pipeline. In an example, feedback obtained may be used to update the solution paths of the NextGen AI engine **102** for the transcription/translation service selection and the input video domain identification.

FIG. **1**B shows a flowchart **1050** that shows a method of translating the input video **110** into a target language in accordance with the examples disclosed herein. The method begins at **1052** with the video translation system **100** receiving the input video **110** along with its metadata. In an example, the metadata can include at least the source language of the input audio track accompanying the input video **110** and the target language into which the input video is to be translated, and optionally any keywords associated with the input video **110**. At **1054**, a domain associated with the input video **110** is identified by the NextGen AI engine **102**. The keywords associated with the input video **110** in its accompanying metadata or if no keywords are associated then, keywords extracted from the input audio track can be used to create a probability scorecard against the plurality of predefined domains. In an example, the Naïve Bayes method can be employed for creating the probability scorecard. One of the plurality of predefined domains with the highest probability can be output as the domain of the input video at **1054**.

The identified domain along with the pair of source and target languages can be used, to automatically select a translation engine from the plurality of translation engines **160** and a transcription engine from the plurality of transcription engines **170** at **1056**. Furthermore, an optical character recognition (OCR) engine can also be employed for extracting textual content displayed in the input video **110**. Accordingly, multiple solution paths with various combinations of the OCR engines that can extract textual content in the source language from the input video **110**, the plurality of translation engines **160**, and the plurality of transcription engines **170** are generated. The different solution paths can be scored based on the accuracy provided by the particular combination of the OCR engine, the translation engine, and the transcription engine. The solution path with the highest score indicative of the highest accuracy is output at **1056** as the automatic selection.

At **1058**, the input audio track is extracted. In addition, various techniques are employed for gender detection, pause detection, and stop word identification. In an example, a dataset can be prepared for several languages, wherein for each language, the dataset contains sample audio clips of different people speaking in different accents, tones, and styles. The audio samples can be converted into Mel-spectrograms that are used to train a gender detection model which includes a deep learning-based convolution neural network (CNN) with long short-term memory (LSTM). The dataset can be divided into a training set, a test set and a validation set for testing and validating the gender detection model. In an example, CNN-based audio segmentation can be implemented to detect the gender in the input audio track. The CNN can be trained to split audio signals into homogeneous zones of speech i.e., voice segments which are then classified based on gender.

Different languages can include different stop words. Accordingly, the dataset can also include samples for training different machine learning (ML) models such as classifiers for stop word identification in different languages. When the source language is identified, the classifiers for stop word identification of the source language can be employed. Identification of stop words further enables detecting pauses in the input audio track. The pauses can also be marked based on the start and end times of the subtitles (if any) in the input video **110**. Transcription of the input audio track is obtained using the selected transcription engine at **1060** in the source language. The transcription is translated into the target language using the selected translation engine at **1062** and voice output can be produced from the translated transcription at **1064**.

Furthermore, meaningful textual content displayed in the source language in the input video **110** is also extracted **1066**. As detailed herein, frames with textual content can be initially identified from the input video **110** by extracting features and using contour detection techniques. Frames with predominant textual content are identified based on a predetermined area of textual content within the frame. Multiple frames with the same textual content are de-duplicated for the extraction of meaningful text.

The translated subtitles are generated at **1068** by translating the transcription of the input audio track and the meaningful text extracted from the input video **110** into the target language using the selected translation engine. An output audio track in the target language is produced at **1070** from the voice output. The output video **190** that displays the video content of the input video **110** in synchrony with the translated subtitles and the output audio track is generated at **1072**.

FIG. **2**A shows a block diagram of the NextGen AI engine **102** in accordance with the examples disclosed herein. When the input video **110** is received, various deep learning models included in the NextGen AI engine **102** can be employed for automatic detection of the language, domain of the input video **110**, and gender of the speakers in different frames of the input video **110**. The translation and transcription services can be selected by the engine selector **202** based on their accuracies for the particular pair of the source/target languages. The glossary selector **204** can select one or more glossaries based on the source/target languages and the particular domain associated with the input video

110. In an example, the selected glossaries may include domain-specific terminologies in the source/target languages. In an example, trained classifiers can be used for the various selections. In an example, the engine selector **202** can implement deep learning models which can be trained on explicitly labeled data for engine selection for particular source-target language pair and domain combinations. The glossary selector **204** can be programmed to select particular glossaries based on the identified domain and the source-target language combination. Optional customizations **206** such as overriding the automatic selections made by the engine selector **202** and/or the glossary selector **204** can be included. Other optional customizations may include sensitive data redaction of the input video **110**, classification and summarization of the input video **110**, etc. The solution path **208** provided by the NextGen AI engine **102** can include a selection of a transcription engine **212** from the plurality of transcription engines **170**, a selection of the translation engine **214** from the plurality of translation engines **160**, and an OCR engine **216** for text extraction from the frames of the input video **110**. Feedback **218** regarding the selected engines can be obtained after providing the output video **190** and may be incorporated into the NextGen AI engine **102** via reinforcement learning.

The NextGen AI engine **102** includes multiple AI algorithms and cognitive services and intelligently recommends the solution path for any input video based on a domain and language pairs. This intelligence is consistently updated based on the latest learnings and user feedback. Following are the high-level steps executed by the NextGen AI engine **102** when a new video translation request is received:

1) Identify the Language, Domain, and Gender in the video. Language detection can be done using inbuilt cognitive services functionalities while for gender detection, customized voice models such as custom CNNs are developed for different languages.
2) Classification models using the domain-specific word-based embeddings are used for the domain identification.
3) The metadata mapping for this information corresponding to the various parts of the particular video is built.
4) The video can be segregated into multiple parts based on the above-captured metadata.
5) The best OCR engine, transcription engine, and translation engine are identified for the corresponding language and domain pairing which provide the highest accuracy and least data leakage for different parts of the particular video.
6) The most appropriate glossary required for the domain-specific translation is selected by a smart recommendation system of the glossary selector **204** which picks the best glossary for the selected language based on the best possible match for the domain-specific words.
7) The solution path is executed and the step outputs are merged for generating the final video output.
8) The NextGen AI engine **102** recommends the solution path which may provide the most accurate results. This intelligence is constantly updated based on an automatic feedback incorporation mechanism.

FIG. 2B shows some of the custom models employed in the NextGen AI engine **102**. The input video keywords **254** along with the glossary words **256** are identified and then a probability scorecard is created against predefined domains. In an example, the keywords **254** and the glossary words **256** can be provided as metadata along with the input video **110**. The Naive Bayes algorithm which is represented by equation **252** can be used to create a probability scorecard **260** against predefined domains and the domain with the highest score is recommended. The glossary recommendation is executed based on a semantic web of keywords **254** created from the input video **110** and an elastic search **258** is carried out from the embeddings of the glossaries defined. The best suitable glossary is selected based on the semantic textual similarity **260**.

FIG. 2C shows a block diagram of the generation of the solution path by the NextGen AI engine **102** in accordance with the examples disclosed herein. The engine selector **202** of the NextGen engine **102** runs various solutions paths with different combinations of a plurality of OCR engines **270**, the plurality of translation engines **160**, and the plurality of transcription engines **170**. A step-wise score is generated for each step of a given solution path. For example, each of the steps **272**, **274**, and **276** of the solution path A1B2C10 is scored and an aggregate score can be generated from individual step-wise scores. Similarly, other combinations may also be generated and scored. The solution path with the highest score e.g., A1B2C10 is recommended as the final path **282**. At every step, the solution with the highest accuracy is picked and a solution path is recommended which ensures the highest accuracy among the available solution paths.

FIG. 3A shows a block diagram **300** of the various steps involved in extracting the text from frames of the input video **110** by the text extractor **106** in accordance with some examples. The input video **110** is initially analyzed **302** in terms of frames e.g., 70 frames per second (fps), or 120 fps, etc. Detection of frames within the video with text is based on deep neural networks (DNNs) and bidirectional Long Short Term Memory (LSTM). Each frame may be considered as an image and AI-based image analysis models can be applied to detect frames with textual content **304** as further detailed herein.

Meaningful text is generally spread over multiple frames, and the text may be displayed for a significant amount of time. In an example, textual content displayed for a predetermined threshold time defined as a percentage of the entire run time of the input video **110** can be identified as a meaningful text that is to be extracted. Accordingly, multiple frames with the same textual content are deduplicated **306** so that one frame forming an image containing a dear rendering of the textual content may be selected during the deduplication **306**. The text is extracted **308** from the frame/image using OCR by employing one of the plurality of OCR engines **270** that was automatically selected in the final path **282**. The extracted text is translated **310** and metadata such as the duration of display of the text and the temporal position of the textual display in the input video **110** may be mapped **312**. After the extraction and de-duplication of the video frames, the input video **110** may be published **3•14** for the next step in the translation processing.

FIG. 3B shows a block diagram **350** shows further details of the steps of identifying text from a given frame implemented by the text extractor in accordance with the examples disclosed herein. The video frames may be initially analyzed via contour detection **352** for the identification of features indicating a likelihood of the presence of textual content in the frames. Then, a source language-based CNN trained in identifying the textual content of the source language can be used to generate an ordered sequence of features **354** indicative of textual content in the contoured image. The source language-based CNN can be trained for predicting letters of the source language and compensates for the errors that may be produced by the process of contour detection, which may misidentify other content, such as geometric figures as textual content. The text area identification **356** is executed for finding the relevant portion or identifying an area of the frame including the textual content. To locate the text region within the frame and to create a bounding box on each letter, a CNN-based architecture can be used which helps to predict the characters. Detecting the textual area within the frame can simplify and improve the speed of the textual identification process. The output from the text area identification **356** is passed through a bidirectional-LSTM to extract word features **358**. Recognition or classification of the textual content **362** can be executed by a recurrent neural network (RNN) trained to classify text based on context. Finally, the extent of the area including the textual content may be used as an attribute in selecting those frames with meaningful textual content. In an example, a percentage of textual features to non-textual features can be calculated. Accordingly, it is determined **364** if the input image **320** has text above a predefined threshold percentage. The video translation system **100** may be configured to identify frames with textual content occupying an area greater than a predefined threshold for a frame to be classified as a textual content bearing video frame. OCR can then be run on the frames having text above the predefined threshold for recognizing the textual content **366**.

A mechanism that detects the change in frames of the input video **110** may be implemented by the video translation system **100** for identifying changes in the textual content of the video frames. It is based on a full convolution network on top of Siamese networks. Rather than implementing a simple classification, the idea of comparing the images by customizing a discriminative implicit metric is proposed. It can be divided into two parts: Firstly, a Siamese Network which is fully convolutional is implemented and the already defined distance metric can be used for discriminating between textual content between frames. This process can be treated as learning a dissimilar function directly on raw images. To summarize, two images can be provided as input with different timestamps to the Siamese neural network. The feature vectors for both images are extracted. It may be noted that the images have to be treated by the same network for feature extraction. The extracted feature vectors are passed through the convolutional layers and finally the Euclidean distance to measure the changes for two feature vectors can be calculated. If there are no substantial changes in the images, the images would have nearly similar feature vectors and if the changes are relevant then the images would have different feature vectors.

It may be appreciated that the video translation system **100** can be configured for the translation and transcription of any given language pair. By way of illustration and not limitation, the video translation system **100** can be configured to translate/transcribe various combinations of languages, such as Japanese to English, vice versa, etc. Accordingly, the video translation system **100** can include many neural networks trained to identify the textual content of the specific languages. Therefore, a neural network trained to identify Japanese scripts may be used in the Japanese to English transcription/translation. Similarly, another neural network trained to identify Arabic or Spanish scripts may be used for any combinations of Spanish, English, or Arabic translations. Any number of neural networks thus trained for different languages can be employed by the video translation system **100** for translating/transcribing between different language combinations.

Traditional techniques like OCR used for recognizing the text from the documents may maintain good accuracy for scanned documents. However, the same techniques cannot be applied for text detection from images such as video frames, due to lower accuracy. The recognition of text from a video scene needs special features because the characters present in the scene may differ in size, shape, color, writing style, orientation, aspect ratio, and quality of the image due to different lighting conditions, blurred and complex backgrounds. Accordingly, the relevant changes for text identification need to be detected while other changes need to be ignored. The methodology implemented for deduplicating the video frames is to be robust enough to account for slightly different orientation/lighting conditions such as those that may occur in images captured using satellites which may be prone to variable cloud covers, sunlight reflection, and changes in the azimuthal and elevational angles of the satellite itself.

FIGS. **4**A and **4**B illustrate a de-duplication of video frames implemented by the text extractor **106** in accordance with some examples disclosed herein. In FIG. **4**A, two images, image **1** and image **2** corresponding to two video frames can be received by a fully convolutional neural network **402** for feature extraction. Feature maps **1** can include features extracted from image **1** and feature maps **2** can include features extracted from image **2**. The pixel-wise Euclidean distance **404** is estimated for the feature maps **1** and the feature maps **2**. A sigmoid function **406** is applied to the result to obtain **408** the similarity. In an example, the similarity is determined to be 0.15. Based on a comparison of the similarity with a predetermined similarity threshold (e.g., 0.5), it can be concluded that image **1** and image **2** are dissimilar.

Similarly, in FIG. **48**, image **1** can also be compared with image **3** corresponding to another video frame. The fully convolutional neural network **402** extracts features to generate feature maps **1** and feature maps **3**. The pixel-wise Euclidean distance **414** between the feature maps is obtained, and the sigmoid function **416** is applied to determine the similarity. Based on a comparison of the similarity value of 0.9 with the predetermined similarity threshold (e.g., 0.5), it can be determined that the video frames corresponding to image •**1** and image **3** are similar and one of the images can be further analyzed while the other image can be disregarded.

FIG. **5** shows a block diagram **500** of the steps involved in generating the output video **190** implemented by the output file processor **136** in accordance with the examples disclosed herein. Initially, the input audio track is extracted **502** by the audio extractor **104** from the input video **110** and the gender of the speaker(s) in the input audio track is detected **504**. The input audio track is transcribed and translated **506** to generate translated text in the target language corresponding to the input audio track. In an example, the text generated at **506** can also include the translation of the input audio track and the text extracted from the video frames of the input video **110**. A speed coefficient is calculated **508** to determine the speed of the translated speech or voice output relative to the video content of the input video **110**. Based on the relative speed of the voice output versus the video content, it is determined **510** if the voice output or the video has to be speeded up or slowed down **512** to be synced with the video. In case the audio or the voice output is too fast, while the video is slower, one or more pauses may be inserted **512** into the voice output to generate an output audio track as detailed further infra. On the other hand, if the video is faster than the audio, additional video frames automatically generated using the Generative Adversarial Network (GAN) can be added to slow down the video content of the input video **110**. The lips of the person speaking in the video are manipulated **514** to sync with the translated audio. The output audio track is merged **516** with the video content (which may be altered with additional, automatically-generated video frames) to generate the output video **190** in the target language.

FIG. **6** shows the architecture **600** for gender detection implemented by the gender detector **142** in accordance with the examples disclosed herein. The gender detector **142** can include a gender model **610**, based on CNN/CNN-LSTM methodologies for gender detection in the input audio track extracted from the input video **110**. The gender can be detected, not only from voice quality comparison e.g., tone but also based on language, accent, style, etc. A data set **602** can be prepared with audio samples of different voices with different tones, accents, and styles speaking a particular language for training the gender model **610** for gender detection in one language. For example, in addition to the tone specific words such as 'he', and 'she' are indicative of gender. Some languages include gender-specific verb forms. The gender model **610** may thus be trained to use such semantic information in addition to the tone for gender detection. The audio samples in the data set **602** are initially converted into Mel-spectrograms. The Mel-spectrograms are preprocessed by shuffling, resizing, and normalizing for a preprocessed dataset **604**. The preprocessed dataset **604** is further divided to form a training set **612**, a validation set **614**, and a test set **616** which are used to generate the gender model **610**. Similarly, different gender models implementing the CNN/CNN-LSTM methodologies can be trained for gender detection in different languages. As mentioned above, a gender model specific to one language may employ a particular type of language data (e.g., particular words e.g., 'he', 'she', etc.) in addition to voice quality for gender detection while another gender model used for another language may use another type of semantic information (e.g., gender-specific verb forms). Once trained for a particular language, the gender model **610** can be evaluated **606** for accuracy, precision/recall using a confusion matrix. The convolution network layers **650** process the audio received as an input spectrogram **620** and identify gender at output layer **630**.

The speed at which the video frames are moved in the input video **110** may not always match the speed at which the target language is spoken which can result in a mismatch of the time durations between audio generated from the translations and the original video. This is because the input video **110** is initially made for the source language and its conversion to the target language can change the speed of the speech, the pauses, and styles. These differences that occur during audio dubbing can be minimized by using a speed coefficient. The formula for deriving the speed coefficient (SC) is shown below:

$$\text{Speed Coefficient } (SC) = \frac{\text{duration of audio segment}}{\text{duration of audio segment from subtitle file}} \quad \text{Eq. (1)}$$

The value of SC determines the speed of the audio. A higher value of SC increases the duration (and decreases the speed) of the translated audio/voice output while a lower value of speed coefficient would decrease the duration (and increase the speed) of the translated audio. A few possible scenarios are discussed below:

a) The translated audio is longer than the original audio: In this case, the SC of the translated audio is decreased by a small value and the video frames of the original video may be extended so that a balanced output is obtained in terms of speed with very few observable changes.

b) The translated audio is shorter than the original audio: In this case, the speed coefficient of the translated audio is increased by a small value and then the pauses are intelligently inserted into the translated audio so that a balanced output is obtained in terms of speed with very few observable changes. Accordingly, a pause file can be generated, and divided into two equal segments. Based upon the duration and the segments, the pauses can be added before and after the generated/translated audio file. Experiments were performed and it was determined that the typical value of speed coefficient can lie between 0.8 to 1.3 for good synchrony between the audio file and the video frames. A bi-lingual text aligner can be used to align the text in the source language with that of the target language. It is used to create parallel corpora for the video translation system **100**. The two languages can also be mapped in different vector spaces. The sentence embeddings may be needed to perform bilingual text alignment. Forced alignment techniques of automatic speech recognition can be used to align the audio with text.

FIG. **7** shows a block diagram **700** including the various steps involved in automatic video frame generation in accordance with the examples disclosed herein. For specific cases, where the audio segment is too fast, the speed can be reduced until the speed coefficient reaches a value of 1.3. As a result of this transformation, the duration of audio may be increased. However, if the duration of the audio is increased sub-optimally, portions of the audio may still be asynchronous with corresponding portions of the video, wherein the video duration becomes less than the audio duration. To overcome this asynchrony, duplicate video frames can be generated **702**. In an example, high-resolution images can be generated by employing Generative Adversarial Networks (GANs). This increases the complexity of the video translation system **100** as the video frame generated using GANs may need to maintain spatial and temporal coherency with the existing frames of the original video i.e., the input video **110**. A video can be considered as an even sequence of points in a latent space where each point corresponds to an individual video frame. Therefore, a video generator can be designed to generate a sequence of points in the latent space and an image generator can be designed that maps the generated points into image space. For the image generator, a temporal shift generator can be designed, which introduces the temporal shifting in the distinct frames of the generator. This shifting mechanism ensures the exchange of information between neighboring distinct frames of the video.

The GAN-generated frames can be added **704** to the input video **110** based upon the extended audio duration. A new audio file i.e, the output audio track can be generated by inserting **706** pauses with the translated audio input i.e., the voice output. The output video **190** can be generated by merging **708** of the generated audio file with the altered video including the GAN-generated frames.

FIG. **8** shows a diagram of a temporal shift **800** inserted into the input video **110** in accordance with the examples disclosed herein. A temporal shift generator enables the addition of video frames to the input video **110** for long voice segments i.e., when at least a portion of the translated audio file has a greater temporal length than the corresponding portion of the input video **110**. The shifting operation can be performed by a temporal shift generator to replace the features of a frame corresponding to the current timestamp ($T_0$) with features from a distinct frame before $T_0$ and a distinct frame after $T_0$. i.e., features from distinct frames that immediately precede and immediately succeed $T_0$ replace features of the frame corresponding to $T_0$. To determine the distinct frames, the edge descriptors of the frames are calculated. Then the Euclidean distances of the neighboring frames from the current frame are calculated. Generally, the threshold value of the Euclidian distance for identifying distinct video frames in any given video was determined as 0.3 from different experiments. Assuming that the distinct frames identified are represented as $T_{d-1}$ and $T_{d+1}$, a temporal shift **800** can be implemented to enable the generation of video frames that fit between the distinct frames.

FIG. **9** shows the architecture of a video generator **900** in accordance with the examples disclosed herein. The video generation architecture of the GAN includes a sequence generator **902**, an image generator **904**, and a video discriminator **910**. After the temporal shift generator **950**, an image generator (IG) **904** comprising 2D convolutions can be added. The image generator **904** receives the information of distinct neighboring frames e.g., frame **0**, frame **1**, etc. The video discriminator **910** may determine if the frames generated by the image generator **904** are usable for the creation of the output video **190**. The video discriminator **910** is designed to include a 2D image discriminator **912** that evaluates the subset of video frames and a 3D discriminator **914** for evaluating all the frames for motion consistency of the video. The video discriminator **910** can therefore provide real-time feedback to the image generator **904** in an iterative process. The video generator **900** including the image generator **904** and the video discriminator **910** may be explicitly trained using training images for the image generation and for determining the quality of images.

FIG. **10** shows a generator **1000** based on GAN in accordance with the examples disclosed herein. The generator architecture for lip-synching using GAN contains two networks, the generator **1000** that generates faces in sync with the audio provided and a discriminator (as described infra) that validates the generated face so that the generated face is in synchrony with the output audio track. The generator **1000** can be trained in an adversarial manner such that the generator **1000** learns to create realistic images that are in sync with the output audio track. The generator network includes an audio encoder **1002**, a face encoder **1004**, and a face decoder **1006**. In addition, posture detection of the face can also be implemented so that the posture can be provided as an input to the face encoder **1004**. It may be appreciated that the details regarding the number of blocks in different networks are e.g., the audio encoder **1002**, the face encoder **1004**, and the face decoder **1006** are shown for illustration purposes only and that more or less number of blocks may be used in the generator **1000** according to the examples disclosed herein.

Referring to the face encoder **1004**, an input ground truth face image **1014** can be provided with a target pose. The lower half of the input ground truth face image **1014** may be masked so that it provides only the information about the pose of the face but not about the shape of the lips. The face encoder **1004** comprises a series of residual blocks with intermediate down-sampling layers and embeds the input ground truth face image **1014** into a face embedding, A CNN network can be used as an audio encoder **1002** that takes Mel-frequency cepstral coefficient (MFCC) heatmap as an input and creates an audio embedding **1008** which can be further concatenated **1016** with the face embedding•**1012** to create a joint audio-visual embedding. The face decoder **1006** produces a lip-synchronized face **1018** from the joint audio-visual embedding by superimposing the masked region of the input ground truth face image **1014** with an appropriate mouth shape. The face decoder **1006** comprises a series of residual blocks with deconvolutional layers for up sampling the feature maps. The output layer **1020** of the face decoder **1006** contains a sigmoid function activated 1×1 convolution al layer with 3 filters. After every up sampling operation at face encoder **1004**, skip connections can be provided between the face encoder **1004** and the face decoder **1006** which ensures that the fine grained facial features are retained by the face decoder **1006** while generating the faces. The face decoder **1006** generates a fake mouth shape matching the given pose that has been fed back to the face encoder **1004** as an input.

FIG. **11** shows the discriminator **1100** for lip-synching using GAN in accordance with the examples disclosed herein. In an example, the discriminator **1100** may be used to encode an input face and audio into fixed representations and computes the L2 distance d between them. The face encoder **1104** and audio encoder **1102** used in the discriminator network **1100** can be the same as those used in the generator **1000**.

FIG. **12** shows the steps involved in generating the translated subtitles in the target language **1200** in synchrony with the input video **110** in accordance with the examples disclosed herein. The voice output is generated from the translated transcription of the input audio track and converted to a Mel-spectrogram **1206**. The steps to automatically generate subtitles in various languages to be displayed synchronously with a given video can be implemented without human intervention. The generation of subtitles is based on language-specific stop words, pause word detection, and gender change. The pauses are detected **1208** within a sentence using a customized CNN, The pause duration is calculated **1210** based on the start and end times given in the subtitles for the input video **110**. The pauses can be added **1212** at appropriate time points in the translated audio track or the voice output. In an example, pauses can be added to the beginning and end of sentences based on the stop words.

In an example, the stop words can be used to determine whether the subtitles need to be divided or broken into separate sentences. Each language may include its own set of stop words which can be different in terms of how the language is spoken versus how the language is written. For example, in English, the stop words or stop characters can include “.”, “!”. “?” while in Japanese the stop words or stop characters can include “o”, “,”. The stop words can also be used for identifying the end of a sentence. CNN-based audio segmentation can be implemented to detect gender in videos. It splits **1204** audio signals or the voice output into homogeneous zones of speech and helps in gender classification.

FIG. **13** shows the steps for automatic feedback incorporation using reinforcement learning **1300** in accordance with the examples disclosed herein. This helps in regularly updating the models based on the feedback without any human intervention. Upon providing the output video **190** to the user, explicit or implicit feedback **1302** may be received from the user on the translation and transcription outputs of the video translation system **100**. In an example, such user feedback can be provided to the NextGen AI engine **102** which provided the initial selection **1306** of the transcription and translation engines. When the number of user comments providing feedback reaches a certain threshold e.g., 1000 user comments, the model retraining **1308** for that language pair and domain is automatically triggered **1304**. In an example, reinforcement learning can output positive or negative rewards based on desirable or undesirable behavior of the machine learning (ML) components. The reinforcement agent starts various experiments **1310** to check the accuracy gain using a newer model (Le., for the NextGen AI engine **102**). The agent collects **1312** a positive reward wherever there is a gain in accuracy and a negative award whenever there is a drop in accuracy. The agent keeps collecting the rewards based on the long-term policy and takes steps so that there is an overall gain in the outcome. When a predefined threshold of positive rewards is achieved by the agent, the models in the NextGen AI engine **102** may be updated.

FIG. **14** shows the incorporation of reinforcement learning **1400** for retraining the NextGen AI engine **102** and the selection of the transcription and translation services. A reinforcement agent can interact with the various environments (or models) associated with different transcription and translation services. Based on the desirable or undesirable behavior of the environment, the agent may collect positive or negative rewards so that if the positive reward is above a minimum threshold, the models are updated and the feedback **1402** is discarded.

FIG. **15** illustrates a computer system **1500** that may be used to implement the video translation system **100**. More particularly, computing machines such as desktops, laptops, smartphones, tablets, and wearables which may be used to generate or access the data from the video translation system **100** may have the structure of the computer system **1500**. The computer system **1500** may include additional components not shown and that some of the process components described may be removed and/or modified. In another example, a computer system **1500** can sit on external-cloud platforms such as Amazon Web Services, AZURE® cloud or internal corporate cloud computing clusters, or organizational computing resources, etc.

The computer system **1500** includes processor(s) **1502**, such as a central processing unit, ASIC or another type of processing circuit, input/output devices **1512**, such as a display, mouse keyboard, etc., and a network interface **1504**, such as a Local Area Network (LAN), a wireless 802.11x LAN, a 3G, 4G or 5G mobile WAN or a WiMax WAN, and a processor-readable medium **1506**. Each of these components may be operatively coupled to a bus **1508**. The computer-readable medium **1506** may be any suitable medium that participates in providing instructions to the processor(s) **1502** for execution. For example, the processor-readable medium **1506** may be a non-transitory or non-volatile medium, such as a magnetic disk or solid-state non-volatile memory, or a volatile medium such as RAM. The instructions or modules stored on the processor-readable medium **1506** may include machine-readable instructions **1564** executed by the processor(s) **1502** that cause the processor(s) •**1502** to perform the methods and functions of the video translation system **100**.

The video translation system **100** may be implemented as software stored on a non-transitory processor-readable medium and executed by the one or more processors **1502**. For example, the processor-readable medium **1506** may store an operating system **1562**, such as MAC OS, MS WINDOWS, UNIX, or LINUX, and code **1564** for the Video translation system **100**. The operating system **1562** may be multi-user, multiprocessing, multitasking, multithreading, real-time, and the like. For example, during runtime, the operating system **1562** is running and the code for the video translation system **100** is executed by the processor(s) **1502**.

The computer system **1500** may include a data storage **1510**, which may include non-volatile data storage. The data storage **1510** stores any data used by the Video translation system **100**. The data storage **1510** may be used to store the input videos, the input and output audio tracks, the transcriptions, subtitles, output videos, and other data that is used or generated by the video translation system **100** during operation.

The network interface **1504** connects the computer system **1500** to internal systems for example, via a LAN. Also, the network interface **1504** may connect the computer system **1500** to the Internet. For example, computer system **1500** may connect to web browsers and other external applications and systems via the network interface **1504**.

What has been described and illustrated herein is an example along with some of its variations. The terms, descriptions, and figures used herein are set forth by way of illustration only and are not meant as limitations. Many variations are possible within the spirit and scope of the subject matter, which is intended to be defined by the following claims and their equivalents.

What is claimed is:

**1**. A video translation system, comprising:

at least one processor;

a non-transitory processor-readable medium storing machine-readable instructions that cause the at least one processor to:

identify a domain associated with an input video including an input audio track in a source language;

automatically select a translation engine from a plurality of translation engines and a transcription engine from a plurality of transcription engines based at least on the domain, wherein to automatically select the translation engine and the transcription engine, the at least one processor is configured to:

generate, using trained machine learning (ML) models, multiple solution paths based on the domain, wherein each of the multiple solution paths includes a unique combination of one of an optical character recognition (OCR) engine, one of the plurality of transcription engines and one of the plurality of translation engines;

score each of the multiple solution paths based on accuracy of each of the OCR engine, the transcription engine, and the translation engine used in the unique combination for the source language, a target language, and the domain; and

select the OCR engine, the transcription engine, and the translation engine from one of the solution paths having the highest score of the multiple solution paths;

produce a transcription of the input audio track in the source language by the transcription engine;

translate the transcription into the target language using the translation engine;

generate translated subtitles in the target language using the translated transcription,

wherein the translated subtitles also include translations for textual content displayed in the source language in the input video;

generate a voice output corresponding to the translated transcription of the input audio track;

produce an output audio track corresponding to the input audio track in the target language using the voice output; and

generate an output video that displays video content of the input video in synchrony with the output audio track and the translated subtitles.

**2**. The video translation system of claim **1**, wherein to identify the domain the at least one processor is to:

extract keywords from the input audio track; and

create a probability scorecard against a plurality of predefined domains using Naïve Bayes method.

**3**. The video translation system of claim **2**, wherein to identify the domain the at least one processor is to:

output one of the plurality of predefined domains with a highest probability as the domain of the input video.

**4**. The video translation system of claim **1**, wherein to generate the translated subtitles, the at least one processor is to:

extract text from the input video using optical character recognition (OCR) techniques; and

translate into the target language, the transcription of the input audio track, and the text extracted from the input video.

**5**. The video translation system of claim **4**, wherein to extract the text from the input video, the at least one processor is to further:

detect frames of the input video with textual content using contour detection techniques;

identify a subset of the frames having more than a predetermined area of textual content as including meaningful text; and

deduplicate the subset of the frames including the meaningful text.

**6**. The video translation system of claim **5**, wherein to identify the meaningful text from the input video, the at least one processor is to further:

for each of the frames including the textual content:

generate an ordered sequence of features using a trained convolution neural network (CNN);

identify an area of the frame including the textual content based on the ordered sequence of features;

predict letters of the textual content using a source language based-CNN trained to identify letters of the source language;

extract word features using a bi-directional Long Short Term Memory (LSTM) based on an output of the source language based-CNN;

calculate a percentage of textual features to non-textual features; and

determine that the frame includes the meaningful text based on a comparison of the percentage with a predefined threshold percentage.

**7**. The video translation system of claim **6**, wherein to de-duplicate the frames the at least one processor is to:

extract respective feature vectors for two of the frames; and

measure a Euclidean distance between the respective feature vectors.

**8**. The video translation system of claim **7**, wherein to de-duplicate the frames the at least one processor is to:

determine similarity between the two frames by applying a sigmoid function to the Euclidean distance; and

deduplicate the two frames by comparing the similarity with a predetermined similarity threshold.

**9**. The video translation system of claim **1**, wherein to produce the output audio track, the at least one processor is to:

identify corresponding gender associated with different portions of the input audio track; and

generate the voice output based on the corresponding gender.

**10**. The video translation system of claim **1**, wherein to generate the output video, the at least one processor is to:

compare a duration of the voice output corresponding to the translated transcription with a duration of the input audio track;

determine that the voice output is asynchronous with corresponding portions of the input video;

calculate a speed coefficient as a ratio of the duration of the input audio track divided by the duration of the voice output; and

manipulate one or more of the voice output and video frames of the input video based on a value of the speed coefficient.

**11**. The video translation system of claim **10**, wherein to generate the output video, the at least one processor is to:

determine that the voice output has a shorter duration than the input audio track;

determine an increase to be achieved in a value of the speed coefficient; and

generate the output audio track by inserting pauses in the voice output before and after voice segments of the voice output, wherein pause durations are determined based on the increase in the value of the speed coefficient to be achieved.

**12**. The video translation system of claim **10**, wherein to generate the output video, the at least one processor is to:

determine that the voice output has a longer duration than the input audio track;

determine a decrease to be achieved in a value of the speed coefficient; and

add video frames to video content of the input video based on the decrease in the value of the speed coefficient to be achieved.

**13**. The video translation system of claim **12**, wherein to add the video frames to the input video, the at least one processor is to:

automatically generate new video frames using a Generative Adversarial Network (GAN) that includes a generator and a discriminator wherein the generator creates images for the video frames which are validated by the discriminator.

**14**. The video translation system of claim **13**, wherein to automatically generate the new video frames, the at least one processor is to:

generate the new video frames based on a received ground truth pose of a speaker imaged in the video frames of the input video, wherein the new video frames include fake mouth shapes with the ground truth pose of the speaker.

**15**. A method comprising:

identifying a domain associated with an input video having an input audio track in a source language;

automatically selecting a translation engine from a plurality of translation engines and a transcription engine from a plurality of transcription engines based on the domain, wherein the automatically selecting comprising:

generating, using trained machine learning (ML) models, multiple solution paths based on the domain, wherein each of the multiple solution paths includes a unique combination of one of an optical character recognition (OCR) engine, one of the plurality of transcription engines and one of the plurality of translation engines;

scoring each of the multiple solution paths based on accuracy of each of the OCR engine, the transcription engine, and the translation engine used in the unique combination for the source language, a target language, and the domain; and

selecting the OCR engine, the transcription engine, and the translation engine from one of the solution paths having the highest score of the multiple solution paths;

producing a transcription of the input audio track in the source language by the transcription engine;

translating the transcription into the target language using the translation engine;

generating a voice output corresponding to the translated transcription of the input audio track;

producing translated subtitles using the translated transcription,

wherein the translated subtitles also include translations for textual content displayed in the source language in the input video;

producing an output audio track in the target language from the voice output; and

generating an output video that displays video content of the input video in synchrony with the output audio track and the translated subtitles.

**16**. The method of claim **15**, wherein producing the output audio track further comprises:

detecting gender of voice segments of the input audio track using a custom Convolutional Neural Network (CNN) with a Long Short-Term Memory (LSTM) network trained on a dataset having audio samples of people of different genders speaking in different languages, different accents, different tones, and different styles.

**17**. The method of claim **16**, wherein training the custom CNN with the LSTM network further includes:

training the custom CNN with the LSTM network for detecting the gender in the source language using language-specific features included in the dataset.

**18**. The method of claim **17**, wherein training the custom CNN with the LSTM network further includes:

converting the audio samples into Mel-spectrograms;

shuffling, resizing, and normalizing the Mel-spectrograms; and

dividing the dataset into a training dataset, a validation dataset, and a testing dataset.

**19**. The method of claim **15**, wherein producing the translated subtitles further comprises:

detecting stop words of the source language from the transcription; and

identifying starting and ending of sentences of the transcription using the stop words.

**20**. The method of claim **17**, wherein producing the translated subtitles further comprises:

selecting a glossary based on the domain, the source language, and the target language, wherein the glossary includes domain-specific terminologies in one or more of the source language and the target language.

**21**. A non-transitory processor-readable storage medium comprising machine-readable instructions that cause a processor to:

identify a domain associated with an input video having an input audio track in a source language;

automatically select a translation engine from a plurality of translation engines and a transcription engine from a plurality of transcription engines based at least on the domain, wherein the automatically selecting comprising:

generate, using trained machine learning (ML) models, multiple solution paths based on the domain, wherein each of the multiple solution paths includes a unique combination of one of an optical character recognition (OCR) engine, one of the plurality of transcription engines and one of the plurality of translation engines;

score each of the multiple solution paths based on accuracy of each of the OCR engine, the transcription engine, and the translation engine used in the unique combination for the source language, a target language, and the domain; and

select the OCR engine, the transcription engine, and the translation engine from one of the solution paths having the highest score of the multiple solution paths;

produce a transcription of the input audio track in the source language by the transcription engine;

translate the transcription into the target language using the translation engine; generate a voice output corresponding to the translated transcription of the input audio track;

generate translated subtitles in the target language using the translated transcription,

wherein the translated subtitles also include translations for textual content displayed in the source language in the input video;

produce an output audio track corresponding to the input audio track in the target language using the voice output; and

generate an output video that displays video content of the input video in synchrony with the output audio track and the translated subtitles.

**22**. The non-transitory processor-readable storage medium of claim **21**, wherein the instructions to generate the output video that cause the processor to:

determine that the voice output is asynchronous with the video content of the input video based on a comparison of duration of the voice output with the input audio track.

**23**. The non-transitory processor-readable storage medium of claim **22**, wherein the instructions to generate the output video cause the processor to:

identify beginning and end of sentences in the voice output based on detection of stop words of the target language; and

generate the output audio track from the voice output by adding pauses at the beginning and end of the sentences in the voice output.

**24**. The non-transitory processor-readable storage medium of claim **22**, wherein the instructions to generate the output video cause the processor to:

generate a new video frame using a generator network of a Generative Adversarial Network (GAN) by:

calculate edge descriptors of video frames that precede and succeed a frame corresponding to a current timestamp;

determine corresponding Euclidean distances between the preceding frames and the frame for the current timestamp as well as the succeeding video frames and the frame pertaining to the current timestamp;

identify as distinct frames, two of the preceding and succeeding frames that immediately precede and immediately succeed the frame corresponding to the current time stamp and having the corresponding Euclidean distances greater than a threshold value; and

replace features in the frame corresponding to the current timestamp with features from the immediately preceding and immediately succeeding distinct frames.

**25**. The non-transitory processor-readable storage medium of claim **24**, wherein the instructions to generate the output video that cause the processor to:

evaluate, using a discriminator network of the GAN, the new video frame for motion consistency.

* * * * *