Abstract—With widespread adoption of AI models for important decision making, ensuring reliability of such models remains an important challenge. In this paper, we present an end-to-end generic framework for testing AI Models which performs automated test generation for different modalities such as text, tabular, and time-series data and across various properties such as accuracy, fairness, and robustness. Our tool has been used for testing industrial AI models and was very effective to uncover issues present in those models.

Demo video link- https://youtu.be/984UCU17YZI

I. INTRODUCTION

AI models are increasingly being used in many real-life applications like criminal justice [1], credit scoring [2] and healthcare [3], [4]. While such models are powerful in solving complex decision making, the trustworthiness of these models remains a big issue for their broad adoption. Due to its effectiveness in finding faults, testing is a popular technique for ensuring the reliability of software systems. However, there has not been a generic/holistic testing framework for testing AI models [5] even though such a system is of utmost importance [6].

Challenges. In this paper, we present our AI Testing framework called AITEST. We first enumerate the research and software engineering challenges while clearly stating the choices related to AI Testing that motivated the design of AITEST.

- Multiple Modalities: Unlike software systems that mainly work on structured data, AI systems apply to both structured (tabular, time-series) and unstructured (text, image, audio, video) data. The algorithms are often modality-specific because of the variations in encodings, distance functions, and data properties.
- Property/Oracle: AI systems demonstrate various issues related to accuracy, fairness, and robustness [5] and therefore, automated testing needs to cover such varied properties. However, accuracy testing requires gold-standard labels which demands much manual effort to curate them. So, the challenge is to devise important metamorphic properties [7] which obviates the need for a test oracle.
- Insufficient Test Data: Current practice only uses a fraction of available data for testing that is often insufficient to uncover faults. Therefore, the challenge is to generate high-coverage realistic test data that is effective at discovering faults. Further, the challenge is to synthesize data from the user-specified data distribution to perform ‘what-if’ testing.
- Interpretability/Explainability: Most AI models are not interpretable and therefore, explaining a fault remains a huge challenge, unlike software systems where whole/partial traces and data dumps can be shown as failure explanations.
- Access. Depending on which stage of AI pipeline the testing appears, the tester gets white-box or black-box access to the model. The black-box access enables techniques to generalize across various types of models, whereas white-box techniques can be more effective in testing as it has access to more structural information.

Other than the usual capability of test case execution, management, and the right user-interface, building an AI testing framework needs to address the following software engineering challenges.

- Flow/Pipeline. The challenge is to define a single end-to-end simple pipeline to test varied types of models and properties.
- Abstraction. Given the variety of properties for AI testing, the definition of the test-case itself is very different. Defining the right abstraction for the underlying data model will make the framework more generic.
- Extensible. Given that new algorithms will keep emerging for AI testing, the framework should expose functionalities to extend the testing capability with minimal effort.

Even with these challenges, there are certain common grounds that help us in generalizing the process of testing the AI models. With this background in mind, we have developed a testing framework which automatically generates test cases to test variety of properties like correctness, fairness, sensitivity, robustness for classification models built on tabular or text data, and prediction models on time-series data. Our tool requires only black-box access to models and is therefore model-agnostic. Using our tool, AI testers as well as model developers can evaluate AI models in a systematic and efficient way, thereby significantly speeding up the end-to-end process of deploying AI models.

In this paper, we describe our framework focusing on software engineering challenges without going deep into the algorithmic aspect of solving the research challenges for which we refer to our previous works [8], [9]. Our tool is part of IBM’s Ignite quality platform [10].

The rest of the paper is organised as follows. In Section II we discuss the system design, architecture and the workflow. Section III briefly describes the functionalities of the underlying algorithms along with a short description of the key results. The related work is briefly mentioned in Section IV. We conclude with a summary and future work in Section V.
II. SYSTEM

In this section, we present 1) the flow/pipeline of AITEST, 2) the underlying data model, and 3) the generic functionalities which makes the AITEST extensible.

**Pipeline.** The pipeline is shown in Figure 1(a). To use AITEST, an AI tester requires 1) an AI model to be hosted as an API which can output the prediction(s) corresponding to one or more sample input, 2) training data which was used to build the model. User first selects the type of model (AITEST supports tabular-data classifier, time-series prediction, text-classifier, conversation-classifier models). Then, the user registers a new model as the part of a project into AITEST by providing model API specification and uploading training data. Alternatively, the user can select an already registered model. In the next step, the user selects the model type-specific properties and necessary inputs (described later) required for each property and some data properties which are going to be considered for multiple test-properties. Users can view the status of the test run which shows the number of test cases generated and their status specific to each property. Once the test run is completed, the user can see all the metrics with some recommended action and subsequently view the failure samples along with some explanation. Users can compare the result of multiple runs for all runs in the project. Note that, the pipeline is the same for all types of models and properties.

**Data model.** Here are some key data model design considerations. Consider three properties - correctness, individual discrimination [11], and group discrimination [12]. Correctness checking involves checking a sample’s prediction against the gold standard. Individual discrimination testing tries to match the predictions of two samples differing only in user-specified fairness attributes (like race, gender, etc.). Finally, group discrimination involves checking whether two groups, defined by fairness attributes, are getting sufficiently similar decisions across all the samples. As evident from these varied checks, the notion of test-case cannot be defined at a sample level (as done for software testing). We, therefore, define test-case as a set of samples along with required reference values that can be evaluated against the model to determine success or failure. A test result is associated with a test case that contains the model predictions along with a boolean value denoting success/failure of the test case. A metric is an expression computed over all test-cases and results. A test-case for correctness contains one sample with gold standard, while for individual and group discrimination, it contains a pair and a set of samples, respectively.

This abstraction also helps to cope with the changes. Say, even if the model changes behind the model API, the system can still evaluate the existing test-cases to generate new test-results and metrics. AITEST can evaluate a newly added metric on top of existing test-cases and results.

The data model is shown in Figure 2. One project can have multiple test-subjects. Each test-subject can have one model, multiple data (either training data or result-visualization data), and multiple data-properties (e.g., list of column names). Each test-property (e.g., correctness) can have multiple metrics (e.g., precision, recall, F-score for correctness) and multiple parameters (e.g., fairness threshold in group-fairness). Multiple run-configurations can be defined for each test-subject where each run-configuration contains a set of properties (like correctness and group fairness), properties-specific parameter values (e.g., for group fairness, a range $R$ is specified with default values $[0.8, 1.25]$), and data specific properties (e.g., list of fairness attributes like age, race and any change in data-distribution for what-if testing). Each run-configuration can be re-used multiple-times, where each test-run will generate one run-collection. One run-collection can have multiple runs, each of which corresponds to a test-property. Each run generates one value for every metric associated with the property (called run-metric) and generates a set of test-cases with test-results.

Note that this abstraction enables us to extend the functionality of the system just by updating the data values in the data-store associated with this data model. For instance, it is possible to add a new property and its corresponding tester by updating the data-store with relevant APIs without any changes to the code. We initialize AITEST in the same manner.

**Functionalities.** In this section, we describe the functionalities of various components of AITEST. The system architecture
is shown in Fig. [1](b). We logically divide the tool into two parts - the framework and the testers. The framework contains a UI, data-store, and interacts with the user-input, model API and testers. The testers are responsible to generate realistic test cases, obtain the prediction of test cases using framework, compute the property metrics, and finally update the framework with metrics, test-cases and results. We describe the framework components in this section, and the functionalities of the tester components in the next one.

- Model Registration: As mentioned earlier, the framework is model-agnostic and views each model as a black-box, the framework exposes a functionality to specify model input as a template where placeholders can be replaced by the generated test data to form the legitimate call to model APIs. To retrieve the label and confidence from the model API response, we use the JSONPath patterns [13]. Using this generic way to create API input and retrieve API output enables AITEST to connect to commercial platforms such as Watson ML, Amazon SageMaker or any custom model API very easily. User can specify additional header information, such as authentication, required to access the API. Note that individual testers do not get access to this confidential information as the framework calls the model API and testers can invoke this functionality through API, thereby preserving privacy as we envision that testers can be developed and hosted by any third party.

- Test Run Configuration: A test run may be configured for any of the currently registered models. Different modalities support different test properties (see Section IIII) and when user selects a set of properties for a run configuration, each tester for a selected property is invoked in a separate thread. Each tester is passed the information regarding the test-subject and the run-configuration.

- Results: The presentation component displays the status of the runs containing the total number of test generated, executed, passed, and failed. Subsequent drill down shows the metrics, failure test cases and the results. Since, test-cases and results contain different information depending on the property, the UI dynamically adapts for every property based on the specification of the property object.

### III. Testing Algorithms

Different testers may be integrated with the framework dynamically by specifying the corresponding test-property, associated parameters and their input format, associated metrics, and the result format. The framework UI renders this information to obtain/display the appropriate input/output. The test properties with their parameters, metrics and test failure conditions are summarized in Table I.

**Tabular.** The testers for different properties generate synthetic data to test the model. The main challenge is to generate realistic data (which follows the same distribution as in the training data). If the user specifies changes in the data distribution in the form of user-defined-constraints (UDC), the synthesis procedure gives more priority to the distribution specified in the UDCs and follows the distribution in training data for the other attributes. Additionally, we devise a coverage criterion called path-coverage, which enables data generation equally among various decision regions. Essentially, AITEST generates a surrogate decision tree model which imitates the behavior of the original model with high fidelity. The realistic test-cases are equally generated in the regions specified by constraints in each path of the decision tree. To generate the realistic data, we infer the marginal and joint distribution constraints underlying the data, update them with UDC (if present), and then efficiently sample from the joint distribution to generate data. The details of the properties and algorithms related to synthetic data are available in [18].

#### Table I

| Test Property | Metrics | Test Failure |
|---------------|---------|--------------|
| Correctness   | Accuracy | Label mismatch with gold standard label |
| Group Discrimination (R) | Disparate Impact (DI) | If DI $\notin R$ |
| Individual Discrimination | Flip-rate | Label mismatch of the two samples |
| Adversarial Robustness | Text Classifier |
| Typo Sensitivity(L) | Flip-rate | Label mismatch of original and transformed sample |
| Noise Sensitivity(L) | |
| Adjective Sensitivity | |
| Tense Sensitivity | |
| Voice Sensitivity | |
| Paraphrase variation | |
| Time Series Forecasting | |
| Small Linear Change (α) | RMSE change ($\Delta R$) | If $\Delta R > \alpha$ |
| Un-ordered data (α) | |
| Large Linear Change (β) | If $\Delta R < \beta$ |

**Text.** Each test property related to text classifier checks if a particular kind of text transformation to an input text results in changing the label. Typically, the transformation should preserve the meaning and thus, the label flip is a failure. The research challenge is to ensure that the text transformation results in a meaningful sentence. AITEST gives the flexibility to input the level of changes for typo and noise insertion (with parameter $L$). The adjective, tense, and voice variation involves parsing a sentence from the training data with Stanford Dependency Parser, identifying the relevant words to change, transform those words, and finally checking the result against a language model [14] to assert the semantic validity of the sentence. For the paraphrase generation, we use a back-translation method that translates the training sentence to 20 different languages and then, translate back to English. The results undergo a pruning that checks the preservation of nouns and verbs (in original or in the form of synonyms) to reduce non-meaningful sentences generated due to back-translation. We also test conversation models (Watson Assistant) where we also check the quality of intent,
entity, and dialog flow. The details are omitted for brevity.

Time series. Generally, it is a real challenge to generate realistic data estimates for future to test the time series forecasting, classification and sequence modeling systems. Hence, metamorphic properties [15] need to be developed which do not require any oracle. Similar to other modalities, the key idea behind such metamorphic properties is to see the effect of various transformations of the input data on the final output of the model. Our testers for the forecasting models are focused on the following metamorphic properties:

- **Small (adversarial) linear change**: When a very small constant \((\text{mean}_\text{first}_\text{order}_\text{difference}/100)\) is added to each record, the RMSE of the forecast should not increase by more than a user-configurable threshold \((\alpha)\).
- **Un-ordered data**: Since a timestamp exists in every test data record, as long as the test data represent a particular time range, the ordering of the records should not matter. If the output changes beyond a threshold \(\alpha\) by changing the ordering of the records, then it is a failure.
- **Large linear change**: By taking the test data into the range far away from the original training data (by adding \(10 + (\max_{\text{training}} - \min_{\text{training}})\) to each record), we expect the model to show large increase in the error. If the error is less than the threshold \(\beta\), it indicates that the model normalizes the input test data which is incorrect.

Evaluation. The text-classifier testers have been used to test 6 client models and in every case, it found issues in the model. The failure test cases were used to retrain the model which then increased the accuracy and robustness of the models. We do not present the details of the models and issues found due to client confidentiality. The testers for classifiers related to tabular data have been extensively tested with models built on open-source data [8]. On average, AITEST generated test cases covers 50% more paths than random data. AITEST-generated tests fail individual discrimination and robustness testing on an average \(\approx 16\%\) and \(\approx 45\%\), resp., more decision paths than the test-split. Synthesis using UDC generates varied test suites which presents significantly different (15% to 194% across properties) test results when compared to test data generated from train-test split.

IV. RELATED WORK

To the best of our knowledge, this is the first tool related to AI testing which covers such a comprehensive set of properties for different kinds of models. Concurrently, Ribeiro et al. created an open-source tool called CHECKLIST which tests various properties of NLP models [16]. There exist multiple techniques for effective testing of individual, group fairness and robustness for tabular data for which we have leveraged our work [8, 9, 12] towards this. To the best of our knowledge, our techniques for black-box testing for time-series forecasting models is a first of a kind. However, we are influenced by the metamorphic properties used in white-box testing of forecasting models in [15].

V. CONCLUSION AND FUTURE WORK

In this paper, we presented an AI Testing Framework that enables the users to perform automated testing of the black-box AI models by synthetic generation of realistic test cases. The framework can test any target model as long as its input modalities are supported. As of now, our implementation supports models trained with tabular, text/plain, text/conversation) and time-series data, but the design is generic enough to accommodate many more modalities. With this framework, we enable the AI testers and developers to test their models effectively irrespective of the lack of a sufficient amount of realistic labeled test data and what-if scenarios.

In future, we plan to add support for testing models on images, videos, audio, and multi-modal inputs. The current implementation only supports black-box testing, which when configured, can be applied to a large number of other similar models of the same type without much change. We will also add support for white-box automated testing of some popular and frequently used models.

Our experimental open-source datasets are available at [https://github.com/aniyaagg/AI-Testing](https://github.com/aniyaagg/AI-Testing) but we are not able to disclose rest of the artifacts because of confidentiality clause.

REFERENCES

[1] J. Skeem and J. Eno Louden, “Assessment of evidence on the quality of the correctional offender management profiling for alternative sanctions (COMPAS),” Unpublished report prepared for the California Department of Corrections and Rehabilitation. Available at: https://webfiles.uci.edu/skeem/Downloads.html, 2007.
[2] D. West, “Neural network credit scoring models,” Computers & Operations Research, vol. 27, no. 11–12, pp. 1131–1152, 2000.
[3] P. Gómez-Gil, J. M. Ramirez-Cortes, S. E. P. Hernández, and V. Alarcón-Aquino, “A neural network scheme for long-term forecasting of chaotic time series,” Neural Processing Letters, pp. 215–233, 2011.
[4] T. Davenport and R. Kalakota, “The potential for artificial intelligence in healthcare,” Future healthcare journal, vol. 6, no. 2, p. 94, 2019.
[5] J. M. Zhang, M. Harman, L. Ma, and Y. Liu, “Machine learning testing: Survey, landscapes and horizons,” IEEE Transactions on Software Engineering, 2020.
[6] No Testing Means No Trust In AI: Part 1, Last accessed 19th Nov, 2020. [Online]. Available: https://www.forrester.com/report/NoTestingMeansNoTrustInAIPart1/-/E-RES153078
[7] S. Segura, G. Frasér, A. B. Sanchez, and A. Ruiz-Cortés, “A survey on metamorphic testing,” IEEE Transactions on software engineering, vol. 42, no. 9, pp. 805–824, 2016.
[8] Data Synthesis for Testing Black-box Machine Learning Models, Last accessed 19th October, 2020. [Online]. Available: https://researcher.watson.ibm.com/researcher/files/n-diptsaha/aitest.pdf
[9] A. Aggarwal, P. Lohia, S. Nagar, K. Dey, and D. Saha, “Black box fairness testing of machine learning models,” ESEC/FSE, 2019.
[10] IBM IGNITE. Last accessed 19th October, 2020. [Online]. Available: https://www.ibm.com/en/services/applications/testing
[11] C. Dwork, M. Hardt, T. Pitassi, O. Reingold, and R. Zemel, “Fairness through awareness,” in ITCS, 2012, pp. 214–226.
[12] IBM AI/360. Last accessed 19th October, 2020. [Online]. Available: https://github.com/IBM/AI360
[13] JSONPath. Last accessed 19th November, 2020. [Online]. Available: https://jsonpath.com/
[14] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “ Bert: Pre-training of deep bidirectional transformers for language understanding,” 2019.
[15] Dwarakanath et al., “Metamorphic testing of a deep learning based forecaster,” in 2019 IEEE/ACM 4th International Workshop on Metamorphic Testing (MET), IEEE, 2019, pp. 40–47.
[16] M. T. Ribeiro, T. Wu, C. Guestrin, and S. Singh, “Beyond accuracy: Behavioral testing of NLP models with CheckList,” in ACL, 2020, pp. 4902–4912.