ISSN 1816-6075 (Print), 1818-0523 (Online)
Journal of System and Management Sciences
Vol. 12 (2022) No. 2, pp. 391-404
DOI: 10.33168/JSMS.2022.0221

A Study of the Automatic Authentication Module to Improve the Consistency of Outsourced Laboratory Test Results

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Abstract. The purpose of this study was to develop a quality control judgment module with the application of machine learning technology to verify the consistency of the results of laboratory tests outsourced by small and medium-sized hospitals that have difficulties in establishing a quality control system. 65,000 diagnostic testing results data were collected for data collecting and cleansing, and data were categorized as delta value and panic value errors, as well as normal values. It was possible to continually accumulate data by generating dummy data for learning by creating a database for the model to systematically learn the 23 types of tests. To determine the consistency of quality control, the critical value for 23 factors that have an impact on the delta check and panic check was analyzed using the random forest algorithm. For performance analysis of the predictive model, accuracy, precision, ROC curve, confusion matrix, and recall were measured and analyzed. This study applied the CatBoost and random forest algorithms for an analysis of the quality control consistency prediction model to obtain sufficient data to train the machine learning algorithms using pre-annotation and data analysis functions for delta check and panic check. The optimized algorithm was learned by applying the LightGBM method to the data that were preprocessed to be suitable for machine learning. To verify the accuracy of the learning results, the test dataset and the empirical dataset were used, and the accuracy of the predictive model was improved through the repetition of machine learning by incorporating the results on quality control consistency in the machine learning model. As a result of analyzing the quality control consistency prediction model, accuracy, ROC curve, precision, F1 score, and recall were all found to be at least 95% or higher, indicating excellence. It is possible to improve the reliability of diagnostic tests by applying an AI-based prediction model to the verification of the consistency of outsourced test results using machine learning techniques. Applying the findings of this study will contribute to the improvement of medical treatment and care to important

values for diseases early on with respect to test results that must be communicated to the doctor immediately.

Keywords: AI (Artificial Intelligence), outsourced laboratory testing, laboratory information system, big data, diagnostic test QC

1. Introduction

Most medical institutions operate various types of medical information systems that are incorporated with advanced Information and Communications Technology (ICT). In laboratory medicine, in particular, a laboratory information system may be in operation for the medical staff to obtain the patient's test results through an Order Communication System (OCS) after various clinical tests are conducted. Laboratory medicine departments are responsible for collecting specimens, conducting clinical pathology tests, verifying and managing the test results, and delivering the verified test results to clinical departments. Diagnostic test results have a significant influence on medical decision-making and are thus essential for accurate treatment and care (Ohkubo 1995). For this reason, laboratory medicine departments are committed to providing accurate and reliable diagnostic test results to the medical staff. Quality control (QC) during clinical pathology tests is particularly crucial for preventing errors that may occur in the process, and it must be carried out in a thorough and stringent manner. Although QC is carried out systematically for clinical pathology tests at university hospitals and major hospitals with abundant capital, facilities, and manpower, small and medium-sized hospitals lack the facilities, manpower, time, and other resources for such systematic QC. In fact, 97.49% of general hospitals in Korea perform QC in relation to clinical pathology tests, compared to only 38.03% of small and medium-sized hospitals. This is due to the fact that many smaller hospitals lack laboratory medicine specialists who can provide verification findings and/or an information system that allows them to make systematic and thorough diagnostic decisions. Recent studies on the QC of diagnostic tests have focused on internal QC methods for detecting errors in test results as well as on possible solutions to the difficulties in real-time QC and delays and increased costs caused by QC. Despite the fact that laboratory medicine departments have utilized numerous QC methods, they have not built a database on the relevant results, making it difficult to use the knowledge in research. As a result, research on this topic has mostly focused on mathematical models for examining the relevance of a sample's entire population using statistical analysis techniques, as well as decision-making systems based on data-driven predictions (Yang 2017). With respect to the QC issues of small and medium-sized hospitals, there has been an increased demand for using diagnostic test results among doctors. There has also been a growing need for advanced information systems to analyze diagnostic test results and support medical decision-making, as well as a medical information system to communicate test results and an intelligent integrated information system that is integrated with laboratory medicine data.

Accordingly, it has been noted that there is a need for a QC automation module to improve the consistency of diagnostic test results. By applying big data analysis and machine learning techniques, it should be possible to enhance the productivity of diagnostic test QC and provide reliable test results that can directly help doctors treat the patients.

In order to assist small and medium-sized hospitals that outsource diagnostic tests to external laboratories due to the difficulties in operating a diagnostic test system and establishing a systematic QC system, this study was carried out to discover key patterns and rules from outsourced test data to detect problems concerning the accuracy of test results and QC. With this, a real-time QC decision module was developed with the application of big data analysis and machine learning techniques. As a result, the goal of this study was to create a QC decision module using big data analysis and machine learning techniques to ensure the consistency of outsourced test results in order to help small and medium-sized hospitals struggling to establish a systematic diagnostic test QC system improve their reliability and competitiveness.

2. Theoretical Considerations

2.1. Concept of outsourced laboratory testing

Outsourced laboratory testing refers to a test of which the results are provided by a third-party institution that has been accredited by the Korean Association of Quality Assurance for Clinical Laboratory as a clinical library for tests cannot be performed by the outsourcing hospital. Among the health screening tests, the ones that commonly get outsourced to an outside laboratory include some of the blood tests that are difficult to carry out within the hospital or the qualitative detection of alpha-fetoprotein (AFP). Tests that cannot be outsourced include BT and CT among ESR, bleeding, and thrombosis tests as well as artery blood gas analysis (ABGA), ammonia test, CK-MB test, and cross-test. In principle, urine tests are not ordered for health screenings. The growth of outsourced laboratory services has been driven by a steady increase in the demand for specimen tests, tests for various infectious diseases, and genetic testing driven by the advances in personalized healthcare at medical institutions and health screening facilities. With the growing importance of preventative healthcare, the focus has shifted to specimen testing, which can lead to disease early detection. In the case of infectious diseases, there has been a growing demand for antibody testing following vaccination for rubella. In the field of cancer treatment, genetic testing for personalized healthcare has been on the rise, and it is gradually becoming one of the biggest outsourced services.

In this study, “outsourced laboratory testing” was defined as a “specimen (blood, urine, tissue, etc.) testing service entrusted by a medical institution, etc.” It is largely divided into an outside laboratory type where the specimen is transported to a testing

center established by the entrusted party and the in-hospital type where the testing equipment inside the hospital is used for the services.

2.2. Diagnostic test QC system

QC refers to the use of a number of scientific and statistical procedures to keep data accurate and precise and to report it. To provide optimum care, the laboratory should conduct clinical tests in reproducible and accurate ways. To this end, the "Guidelines and recommendations for laboratory analysis in the diagnosis and management of diabetes mellitus" published in Clinical Chemistry in 2002 is widely applied (David et al., 2011). The precision of diagnostic test results can generally be improved by internal QC activities and compliance with laboratory operation guidelines. Although the laboratory itself can monitor the coefficient of variation, the bias can only be measured and evaluated based on a comparison of test results using standard methods by an accredited institution. QC techniques can be divided into internal QC and external QC. External QC involves sending the same sample to several laboratories for analysis and comparing the results submitted by individual laboratories. Examples of external QC at home and abroad are the laboratory credibility survey of the Clinical Chemistry Subdivision of the Korean Association of Quality Assurance for Clinical Laboratory and proficiency testing (PT) of the College of American Pathologists (CAP). Both institutions set the average of the reported values of a peer group (a group using the same test method or equipment) as the target value and quantitatively manage the degree of error in the values reported by each laboratory. This external QC method is based on a report that the average test values of laboratories performing QC activities is similar to the theoretical true value measured using the standard test method (Ross 1988; Tholen 1993; Hartmann 1985; Ross 1998). For this type of external QC, methods using the standard deviation index (SDI) and variance index score (VIS) are mainly applied. Internal QC involves evaluating precision and accuracy by managing the primary fluctuations in the machinery and test results of the medical institution in question. With this, the QC material and method are documented for each test, and it is carried out in accordance with the principles. The results are then approved after a review by the tester, manager, and professor in charge. Internal QC is divided into precision control and accuracy control. Precision control methods include a method that uses control samples, a method that does not use control samples, a method that uses a commercially available freeze-dried product for QC, and a pooled serum method that uses products produced inside the laboratory for QC. Accuracy control methods include a comparison of standard serum test data, additive recovery rate test, and a comparison with the standard method.

The purpose of this study was to verify the precision of outsourced laboratory test results by using the results verified by the entrusted laboratory in order to establish a QC system for medical institutions that are unable to set up their own laboratory test system and must outsource them to external laboratories. To improve the precision of

test results, delta check and panic check were used as methods of managing individual samples to automatically check whether differences in results, if any, were due to changes in the patient's condition or an error.

2.3. Concept of delta check

Delta check is a way of observing the difference between the previous test result and the subsequent test result for the same patient. If the difference exceeds the relevant limit, it may be due to a sample error, analytical error, or change in the patient's condition. Delta check is an essential means to improve the quality of the test performed by discovering an error or problem so that pp prompt action can be taken to mitigate it. Numerous errors and problems prior to a test cannot be identified by the typical QC methods alone, which is why incorrect test results are reported in some cases. In other words, mislabeling, clerical error, and sample collection from the IV line among other problems cannot be overlooked unless a delta check is performed to check for meaningful changes in the test results. The delta variance for various tests is determined by the laboratory, and examples of general chemistry test values are shown in <Table 1>.

Table1. Examples of general chemistry test values

Check Item	Delta Limit
Albumin	2.0 g/dL
*Bun	25.0mg/dL
Carbon Dioxide	15 mEq/L
*Creatine	10 mg/dL
Osmolality	20 mOsm/kg
Sodium (Na)	15 mEq/L
**Uric Acid	2.0 mg/dL
Bilirubin	2.0 mg/dL
Calcium (Ca)	3.0 mg/dL
Chloride (Cl)	15 mEq/L
Magnesium	2.0 mEq/L
Potassium (K)	2.5 mEq/L
Total Protein	2.0 gm/dL
*Non-Renal, ** Non-Heme/Onc	

It is necessary for each laboratory to use an appropriate delta check method and standards to increase the error detection rate, while minimizing the workload. There are four factors that can be examined to perform the delta check: the delta difference, delta percent change, rate difference, and rate percent change (Edward 2019). Although there is no set standard for choosing which method to apply, the delta difference and width of the reference range have recently been recommended because they are practical and intuitive, and it is easy to check the changes in the results by

reflecting biological variations in the tests and the patient characteristics (Park et al., 2012).

2.4. Concept of panic check

A panic check refers to a system that allows test results, which can indicate fatal consequences for the patient, to be immediately reported to the clinician. It involves checking whether a test result has significantly deviated from the normal range to a point where the patient's life is threatened, followed by an investigation into the cause and a retest for confirmation. Critical value, which is used synonymously with panic value, is also used to determine whether a patient has a life-threatening disease or is experiencing serious complications that can result in fatal consequences if it is not treated immediately. Standards related to panic values should be set by each laboratory, and panic values should be reported according to the testing system. However, designating too many panic values should be avoided to prevent overwhelming the laboratory or clinicians. A Critical Value Report (CVR) should be issued by the tester to inform the clinician of the results or to request the clinician to check the results in case immediate reporting is necessary or a result that is clinically significant needs to be double-checked. The cases requiring the issuance of a CVR are shown in <Table 2>.

Table 2: Examples of CVR(critical value report)

Check Item		Panic value (lower limit)	Panic value (upper limit)
Blood chemistry	Glucose	30 mg/dL	700 mg/dL
	Calcium	6.0 mg/dL	14.0 mg/dL
	Phosphorus	1.0 mg/dL	8.5 mg/dL
	Sodium(Na)	110 mMol/L	160 mMol/L
	Potassium(K)	2.0 mMol/L	8.0 mMol/L
	Chloride(Cl)	80 mEq/L	130 mEq/L
	BUN	-	80.0 mg/dL
	Creatine	-	6.0 mg/dL
	CK	-	500 IU/L
Blood (general)	WBC	-	100,000/uL above
	Hb	5 g/dL below	19g/dL above
	PLT	20,000/uL below	1,000,000/uL above
	WBC differential count		
Blood coagulation	PT	-	INR4 above
	aPTT	-	120 sec above
	Bleeding time	-	10 min above
Urine	Ketone 3+ & glucose – (limited to pediatric patients)		
Microbial	Blood culture(Gram stain)	Positive	

	AFB stain	
	AFB culture & ID	
	CSF Gram stain	
	CSF culture	
	CSF Cryptococcus Ag	
	CSF latex agglutination	
Blood bank	ABO + Rh	Not consistent with the previous result
Molecular / Genetic	PML – RARA	Positive

2.5. Concept of AI(Artificial Intelligence)

Artificial intelligence (AI) refers to the intelligence possessed by computers with the ability to learn reason, perceive, and search, which have been considered as abilities unique to humans (Kim 2011). The term was first used at the Dartmouth Conference in 1956, when inference and search were key issues in related research. (Priyopradono, 2013). The field of AI went through a period of stagnation until the early 1990s and welcomed a period of revival in the late 1990s with active research on the development of the Internet and machine learning. In the era of the Fourth Industrial Revolution, AI has become a major field of research along with the Internet of Things (IoT), cloud computing, and big data. This type of research has had a significant impact on the industrial sector, and the outcomes have been applied to various fields such as industrial robots, precision medicine, and automatic operation using intelligent learning models (Lu 2017). According to a report on the latest technology trends related to artificial intelligence from Forbes, AI technology was defined as virtual agents, deep learning platforms, robot process automation, machine learning platforms, biometrics, neural networks, text analysis, natural language generation, text analytics and natural language process, voice recognition, etc. (Gill Press, 2017).

This study was carried out to provide quality healthcare services and pursue technological development by applying text analysis and a machine learning platform among various technologies related to AI, including the aforementioned technologies, to the healthcare industry.

2.6. Concept of LightGBM

“Big data” is defined as “next-generation technology and architecture designed to extract value from various types of data at low cost and to support ultra-high-speed collection, discovery, and analysis of data” (John 2011). It is focused not only on collecting and storing data but also on analyzing data and generating and visualizing valuable data.. The big data analysis techniques that are mainly used are text mining, network analysis, and clustering analysis (Park 2013). In this study, text mining and network analysis were applied, and the details of each method are described below.

LightGBM, short for Light Gradient Boosting Machine, is a gradient boosting framework that uses tree-based learning algorithms. A GBM proceeds by adding weight value to the incorrect parts nd boosting creates multiple trees (or other models), but unlike techniques such as random forest or bagging, improvements are made steadily by aggregating the existing prediction results. In the case of LightGBM, the trees grow vertically, whereas other algorithms grow the trees horizontally. That is, LightGBM grows its trees using the leaf-wise strategy. By continuously dividing the leaf node with the maximum data loss, the depth of the trees increases, and an asymmetric tree is created. However, by repeating the division of the leaf node with the max data loss, the prediction error loss can be ultimately minimized further compared to the division of a balanced tree. LightGBM grows trees leaf-wise, as shown in [Figure 1], while other algorithms grow trees level-wise. The biggest advantage of leaf-wise tree growth is that it is fast. LightGBM is thus capable of handling large amounts of data and requires relatively less memory for execution. Another reason behind the popularity of LightGBM is that the focus is on the accuracy of the results. It also supports GPU learning, which is why LightGBM is widely used by data scientists when developing data analytics applications. LightGBM is not recommended for small data sets because it is sensitive to overfitting and can easily overfit small data. There are no restrictions on the number of rows, but it is generally recommended to use LightGBM for data with 10,000 or more rows (Guolin Ke 2017).

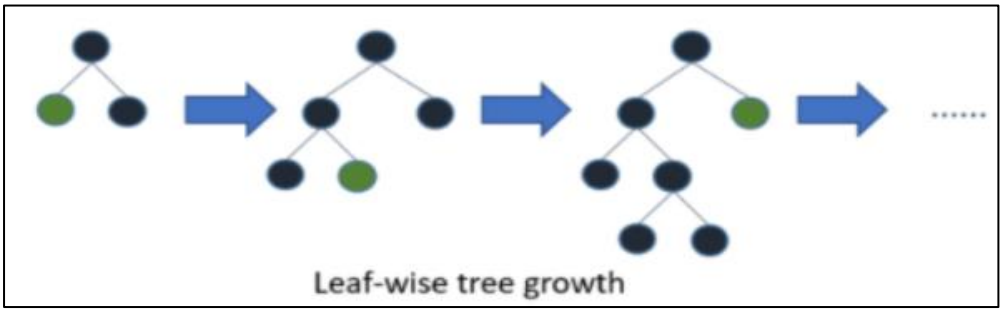

Figure 1. Tree growth by LightGBM

3. Research Method

This study was aimed at judging the consistency of test results in real-time by analyzing diagnostic test results with the application of LightGBM, a big data analysis technique. The research procedure for the development of the target model is shown in [Figure 2].

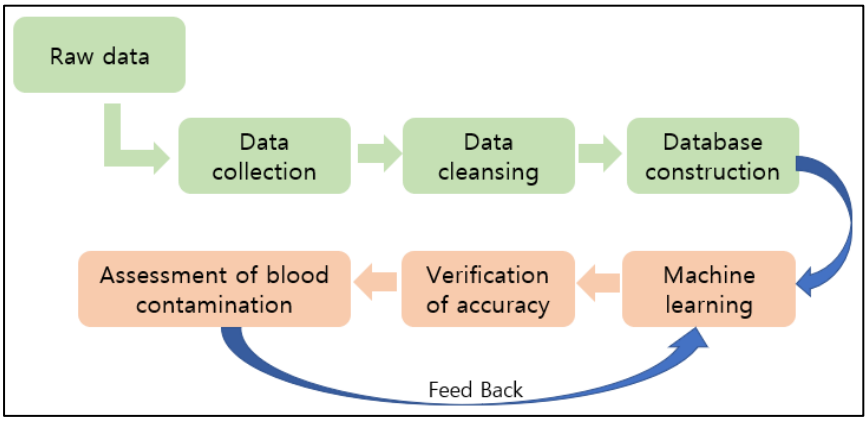

Fig. 2: Big data analysis procedure

First, for the purpose of data collection and cleansing, 65,000 pieces of diagnostic test results were collected. The data were classified as delta value, panic value, and normal data, and dummy data for learning were generated. Second, a DBMS for systematic learning of 23 types of test data was set up to enable gradual accumulation of data. Third, since a large amount of data is required to learn machine learning algorithms, a distribution function was set based on the data obtained in the data generation process. In this process, it was necessary to augment data to prevent impact on machine learning algorithms, even when there were no secondary diagnostic test results, by referencing the results of feature extraction performed in the data preprocessing process. Thus, by forming a distribution function for the results of each of the 23 diagnostic tests and generating tens of thousands of virtual data to maintain the correlation between these distributions and their independence, sufficient data were obtained to train the machine learning algorithm as quickly as possible. Fourth, accuracy was verified using a training set and a test set. Fifth, as part of the process of developing machine learning algorithms and machine learning, the data and system development required for this study were completed by determining the structure of a machine learning program suitable for the data, conducting training, and then repeating the process with the results as feedback.

To construct a prediction model, Excel was utilized for data analysis, the processed data was examined using the CatBoost algorithm, and a decision tree analysis algorithm using test factors and demographic factors was applied. For predictive model performance analysis, TP rate, FP rate, accuracy, precision, and receiver operating characteristic (ROC) area indicators were used to measure and analyze the performance of each predictive model. In order to measure and analyze the performance of the machine learning prediction model, it is necessary to understand the meaning of true positive (TP), false positive (FP), false negative (FN), and true negative (TN), which were used to analyze accuracy, recall, precision, F-measure, and the ROC area to measure performance.

3.1. Analysis of quality control consistency prediction model

The rate of error in delta values and panic values for verification of the consistency of the QC using the dataset was 43%, based on which the data were deemed useful for the predictive model design and appropriate as data for developing a predictive model. To determine the consistency of quality control, the critical value for the 23 factors that would have an impact on the delta values and panic values was analyzed using the random forest algorithm. In order to apply LightGBM to use the data for a hold-out test, the program shown in <Table 3> was created to save the data by learning in case there was no learning model. The accuracy analyzed using LightGBM was found to be high at 0.99, as shown in [Figure 3].

	precision	recall	f1-score	support
0	0.99	0.98	0.99	26869
1	0.98	0.99	0.99	28149
accuracy			0.99	55018
macro avg	0.99	0.99	0.99	55018
weighted avg	0.99	0.99	0.99	55018

Figure 3. Random forest analysis results

As a result of analyzing the ROC curve, which is a method of evaluating the performance of the binary classifier system, the AUC was found to be 0.87, as shown in [Figure 4], indicating that high predictive power

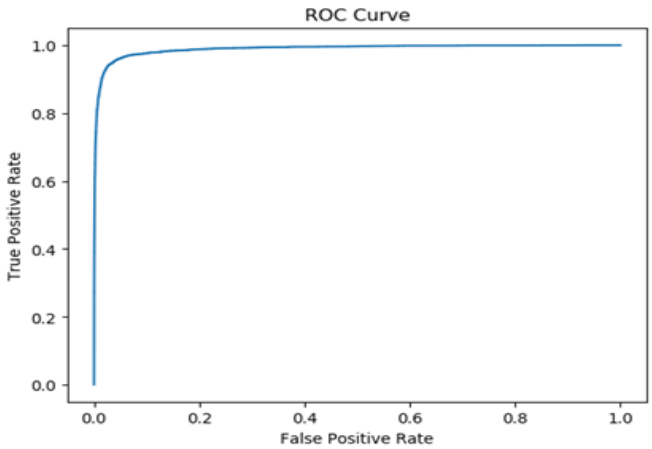

Figure 4. ROC curve for the Diagnostic Test QC

The results of the confusion matrix analysis are shown in [Figure 5], with a TP rate of 0.99, FP rate of 0.01, TN rate of 0.99, and FN rate of 0.01. Precision and recall

were 0.99 and 0.98, respectively, indicating excellent predictive power for consistency

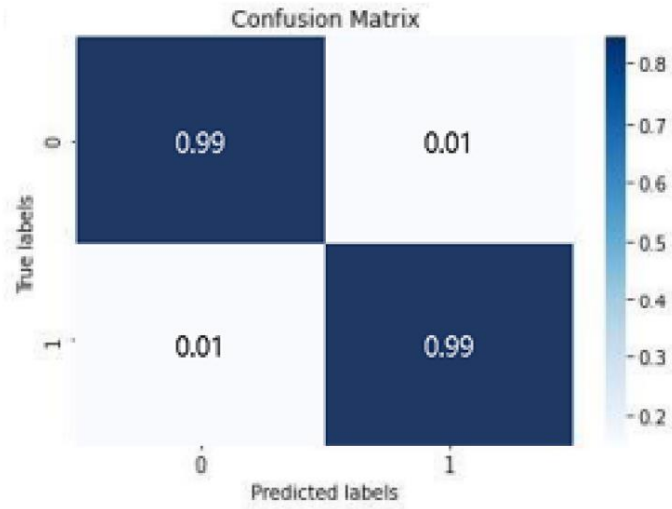

Fig. 5: Confusion matrix for verifying consistency

3.2. Result

Accuracy (%), ROC curve (%), precision (%), recall (%), and F1 score (%) were used as indicators to determine the consistency of QC through a delta check and panic check for the purpose of improving the accuracy of diagnostic tests. For the QC consistency prediction model, CatBoost and random forest algorithms were applied to process 23 types of diagnostic test factors for delta check and panic check, and sufficient data for machine learning algorithm training were obtained using the pre-annotation and data analysis functions. The optimized algorithms were trained by applying LightGBM suitable for the data that have been preprocessed for machine learning. To verify the accuracy of the learning results, accuracy was verified using the test dataset and the empirical dataset, and the relearning of the results data was carried out by reflecting the QC judgment result in the machine learning model. An analysis of the QC consistency prediction model showed terms of accuracy (99%), ROC curve (99%), precision (99%), F1 score (99%), and recall (98%). This study showed that the consistency of QC was excellent at 99%.

4. Conclusion

This study was carried out to perform delta check and panic check as internal QC methods in order to internally verify the consistency of the results of outsourced laboratory tests. In order to judge consistency, machine learning-based AI technology was applied. For the purpose of predictive model development and performance evaluation, the data collected were divided into training data and test data, and

random forest analysis algorithms were used for the predictive model. The indicators examined for performance analysis were accuracy, ROC area, confusion matrix, precision, and recall. As a result of the predictive model analysis, the QC consistency accuracy was found to be over 99%, which was judged to be excellent for application as a commercial platform model. There are several ways to perform QC, but this study was aimed at providing an internal QC solution using AI among ICBM technologies of the Fourth Industrial Revolution to medical institutions facing difficulties in operating laboratory medicine departments on their own. This is expected to enable early detection of abnormal values in the test results so that measures can be implemented to improve the reliability of the medical institution and to boost satisfaction among doctors by enhancing the reliability of diagnostic test results. As a result of verifying the performance analysis of the learning module algorithms that were based on the LightGBM technique, the prediction model was found to be significant at about 99%, on average. The study's findings suggest that medical institutions that are unable to conduct quality control in their diagnostic laboratories on their own can improve their competitiveness by verifying the results of outsourced laboratory tests, thereby improving the test results' reliability and the medical environment. Also, it enables AI analysis of outsourced test results and a critical value check so that the test results that need to be reviewed immediately can be communicated to the relevant doctor in combination with a laboratory information system (LIS). By applying this independent system in the clinical setting, it will be possible to improve the efficiency of medical treatment and care.

One limitation of this study is that the delta value categorization for diagnostic test results was not subdivided into the data gathered; therefore the precision and recall results may have been overstated. As a result, further research is required to determine whether the predictive model results were overestimated by splitting the delta value for the obtained data.

Acknowledgment

This research was supported by the National Research Foundation of Korea(NRF) grant funded by the Korean government(MSIT) (NRF-2019R1G1A1099953)

References

Priyopradono, B., Manongga, D., Herry Utomo, W. (2013). Spatial Social Network Analysis: Program Pengembangan Usaha Agribisnis Perdesaan (PUAP) or an Exertion Development Program in Supporting the Region Revitalization Development. *Social Networking*. 2(2), .63-76. http://dx.doi.org/10.4236 /sn.2013.22008

Sacks, D. B., Arnold, M., Bakris, G. L., Bruns, D. E., Horvath, A. R., Kirkman, M. S., Lernmark, A., Metzger, B. E., & Nathan, D. M. (2011). Guidelines and

recommendations for laboratory analysis in the diagnosis and management of diabetes mellitus. *Diabetes Care*. 34(6), 61-99. doi:10.2337/dc11-9998.

Edward, W., Randell, Sedef Yenice., (2019). Delta Checks in the clinical laboratory. *Critical Reviews in Clinical Laboratory science*. 56(2), 75-97. doi:10.1080/10408363.2018.1540536.

Gill Press. Top 10 Hot Artificial Intelligence (AI) Technologies. Forbes, 2017. https://www.forbes.com/sites /gilpress/2017/01/23/top-10-hot-artificial-intelligence-ai-technologies/?sh=1560f1c71928

Ke, G., Meng, Q., Finley, T. Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T. Y. (2017). LightGBM: A highly efficient gradient boosting decision tree. 31st Conference on Neural Information Processing Systems (NIPS 2017), 1-9. https://papers.nips.cc/paper/2017/file/6449f44a102 fde848669bdd9eb6b76fa-Paper.pdf

Hartmann, A. E. (1985). Accuracy of creatinine results reported by participants in the CAP Chemistry Survey Program. *Archives of Pathology & Laboratory Medicine.* 109(12), 1068-1071.

Park, H. -J., Gwon, Y. –H., & An, Y. –M. (2013). Big data and big data refining technology. *Korean Society Of Computer And Information Review*. 21(1), 1-8. http://www.dbpia.co.kr/journal/articleDetail?nodeId=NODE 06530283

Lu, H., Li, Y., Chen, M., Kim, H., & Serikawa, S. (2017). Brain Intelligence: Go Beyond Artificial Intelligence. *Mobile Networks and Applications*. 23(2), 368-375. https://doi.org/10.48550/ arXiv.1706.01040.

Gantz, J. & Reinsel, D. (2011). Extracting Value from Chaos. *IDC's Digital Universe Study*. 2011.

Ross, J. W. (1988). Evolution of evaluation criteria in the College of American Pathologists Surveys. *Archives of Pathology and Laboratory medicine*. 112(4), 334-339.

Kim, S. Y. (2011). The current situation and the suggestions of AI & Law research in Legal Reasoning. *IT and Law Research*. 5(1), 319-346.

Kim, Y. S. & Yoo, H. (2021). An Analysis of Preference for Nonverbal Communication Methods of Social Robots. *International Journal of Hybrid Information Technologies*. Global Vision Press. 1(1), 61-68, doi:10.21742/IJHIT.2021.1.1.05.

Ohkubo. A. (1995). Strategy for getting many experts in clinical pathology. *Rinsho Byori-Japanese Journal of Clinical Pathology*. 1995 Oct; 43(10): 1010-1013.

Ross, J. W., Miller, W. G., Myers, G. L., and Praestgaard, J. (1998). The accuracy of laboratory measurements in clinical chemistry: A study of 11 routine chemistry analytes in the College of American Pathologists Chemistry Survey with fresh frozen serum, definitive methods, and reference methods. *Archives of Pathology & Laboratory Medicine.* 122(7), 587-608.

Park, S. H., Kim, S. Y., Lee, W., Chun, S., & Min, W. –K. (2012). New Decision Criteria for Selecting Delta Check Methods Based on the Ratio of the Delta Difference to the Width of the Reference Range Can Be Generally Applicable for Each Clinical Chemistry Test Item. *Ann Lab Med*. 32(5), 345–354. doi:10.3343/alm.2012.32.5.345

Tholen, D. W. (1993). Reference values and participant means as targets in proficiency testing. *Archives of Pathology & Laboratory Medicine*. 117(9), 885-889.

Yang, J. Y. (2017). Machine-learning-based Management Prediction Systems using the Corporate Financial Information [dissertation]. [Seoul]: Hansung University, http://hansung.dcollection.net/public_resource/pdf/000002317528_20220310105157.pdf

Wang, W, & Siau, K. (2019). Artificial Intelligence, Machine Learning, Automation, Robotics, Future of Work and Future of Humanity: A Review and Research Agenda. *Journal of Database Management*. 30(1), 61-79. DOI:10.4018/JDM.2019010104