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(Редакциялық-баспа бөлімі)
Тел.: 8(7142) 51-11-76

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(Редакционно-издательский отдел)
Тел.: 8(7142) 51-11-76

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Nam, D.,
PhD Student, senior lecturer,
Kazakh British Technical University,
Almaty, Republic of Kazakhstan

APPLICATION OF GENERATIVE ADVERSARIAL NEURAL NETWORKS FOR LUNG CANCER CT IMAGE SEGMENTATION

Abstract

Lung cancer remains a leading cause of cancer-related mortality, necessitating advancements in early detection and diagnostic tools. This study explores the application of Deep Convolutional Generative Adversarial Networks (DCGANs) to augment CT imaging datasets for lung cancer segmentation. Using a combination of local Kazakhstani and re-labeled LIDC-IDRI data, DCGAN generated realistic synthetic images, improving segmentation performance. The U-Net model, evaluated with the DICE metric, showed enhanced accuracy, with scores improving from 0.3708 to 0.4191. While DCGAN demonstrates strong potential in addressing data scarcity, its high computational demands remain a significant challenge.

Key words: *DCGAN, lung-cancer segmentation, image processing, computer vision.*

1 Introduction

Lung cancer remains one of the leading causes of cancer-related mortality globally, underscoring the critical need for early and accurate diagnostic tools. Despite advancements in imaging technologies, late-stage detection continues to challenge effective treatment and outcomes. Medical imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) play pivotal roles in the detection, staging, and monitoring of lung cancer. However, the reliance on large, annotated datasets for training computer-aided diagnostic (CAD) systems has highlighted the pressing issue of limited data availability.

To address these limitations, data augmentation methods have emerged as a key solution. Traditional augmentation techniques, including rotation, flipping, and noise addition, enhance dataset diversity but often fail to introduce new, meaningful patterns. In this context, advanced machine learning techniques, particularly Generative Adversarial Networks (GANs), have shown exceptional promise. By generating realistic synthetic images, GANs not only expand the dataset but also capture intricate patterns critical for improving model performance. This study explores the application of GANs, specifically Deep Convolutional GANs (DCGANs), for augmenting lung cancer imaging datasets to enhance segmentation performance.

The advent of Generative Adversarial Networks (GANs) [1] has revolutionized various fields of artificial intelligence, offering unprecedented capabilities in generating realistic synthetic data. In the domain of medical imaging, GANs have emerged as a powerful tool with the potential to address numerous challenges and enhance the quality of healthcare delivery. This chapter delves into the application of GANs for medical image generation, exploring their theoretical underpinnings, practical implementations, and transformative impact on medical research and clinical practice.

Medical imaging is a cornerstone of modern diagnostics, playing a critical role in the detection, characterization, and monitoring of diseases. However, the acquisition of high-quality medical images is often constrained by factors such as limited data availability, high costs, and the need for extensive expert annotation. These challenges have spurred interest in developing methods that can generate synthetic medical images, augmenting existing datasets and facilitating advancements in machine learning models used for diagnostic purposes.

The application of Generative Adversarial Networks (GANs) in medical imaging extends beyond simple data augmentation. GANs have been utilized in various innovative areas, including anomaly detection [2-3], image-to-image translation [4-5], and the generation of synthetic medical data [6-7].

Despite their potential, the use of GANs in medical image generation faces several challenges. These include model instability, mode collapse, and the need for significant computational resources. Additionally, ethical concerns related to the generation of synthetic medical data, such as patient privacy and the potential for misuse, require careful attention. This chapter aims to provide a comprehensive overview of the capabilities and limitations of GANs in medical imaging.

The following sections explore the foundational principles of GANs, review state-of-the-art applications in medical imaging, and discuss future directions in this rapidly evolving field. Combining theoretical insights and practical examples, this chapter seeks to highlight the transformative potential of GANs in advancing medical imaging and improving patient care.

The authors of [8] proposed the GAN-LSTM-3D method for reconstructing lung tumors in three-dimensional space from 2D CT images. In this approach, 2D CT images are initially processed through VGG Net [9] to extract features. These features are then fed into an LSTM network [10], which is designed to handle sequential data and capture temporal dependencies. The output of the LSTM is subsequently used as input for a GAN, which reconstructs the lung tumor in 3D space. This method combines the advantages of LSTM for processing continuous data and GANs for generating realistic 3D reconstructions from sequential 2D data. The integration of GAN and LSTM for lung tumor reconstruction was also described in [11]. GANs can also be employed for domain adaptation, such as converting CT images to MRI, as demonstrated in [12].

Unlike the methods discussed above, which focus on reconstructing existing lung cancer images, the authors of [13] used GANs to generate synthetic lung cancer images. They applied Deep Convolutional GAN (DCGAN) to create synthetic lung cancer regions, focusing specifically on cancer-affected areas rather than the entire lung. The generated images were shown to clinicians, who were tasked with distinguishing them from real images. In most cases, the clinicians could not visually differentiate between real and GAN-generated images, demonstrating the high realism achieved by the model.

The authors of [14] also proposed using GANs for synthetic cancer image generation, focusing on a 64x64x64 volume of interest (VOI) near the lung cancer region. They introduced a two-step framework for lung segmentation, combining a Style-based GAN [15] for image generation with a U-Net architecture [16] for segmentation. This approach improves the accuracy and realism of synthetic cancer images, enhancing the training and validation of diagnostic models.

The process of generating lung tumors using GAN-based models was further explored in [17]. The authors employed StyleGAN [18] and pix2pix [19] GANs to synthesize lung cancer images. Similar to previous studies, they focused on the VOI to generate detailed and realistic cancer regions. To evaluate the quality of the generated images, subjective assessments were performed by clinicians, who sketched the synthesized images for realism comparison, alongside objective image quality metrics.

GAN-based models have also been applied in preprocessing and improving the quality of medical data. For instance, CycleGAN [20] has been used for denoising CT images of the lungs, as demonstrated in [21]. GAN-based approaches have also been employed for data anonymization, as in [22], among other applications.Overview of lung cancer

Lung cancer is one of the most prevalent and deadly types of cancer worldwide, representing a leading cause of cancer-related mortality. Despite advancements in medical imaging, diagnostics, and treatment, the prognosis for lung cancer patients often remains poor, primarily due to late-stage diagnosis. The disease is broadly categorized into two main types: non-small cell lung cancer (NSCLC), which accounts for approximately 85% of cases, and small cell lung cancer (SCLC), which is more aggressive but less common. Early detection and accurate diagnosis are critical to improving survival rates, highlighting the importance of advanced diagnostic tools and methods.

The primary risk factor for lung cancer is tobacco smoking, which is associated with nearly 85% of cases. Other significant contributors include exposure to secondhand smoke, occupational hazards such as asbestos and radon, environmental pollution, and genetic predisposition. Chronic lung diseases, such as chronic obstructive pulmonary disease (COPD), and a history of prior lung infections also increase susceptibility. While smoking cessation programs have led to a decline in lung cancer rates in some populations, the incidence remains alarmingly high in many parts of the world, particularly in regions with high smoking prevalence and poor air quality.

Lung cancer is often asymptomatic in its early stages, which complicates early detection. When symptoms do appear, they are frequently nonspecific and can include a persistent cough, chest pain, shortness of breath, unexplained weight loss, and hemoptysis (coughing up blood). These symptoms often overlap with other respiratory conditions, leading to delayed diagnosis and treatment. By the time lung cancer is diagnosed, it is commonly in advanced stages, where curative treatment options are limited.

Medical imaging plays a vital role in the detection, staging, and monitoring of lung cancer. Common modalities include chest X-rays, computed tomography (CT) scans, positron emission tomography (PET) scans, and magnetic resonance imaging (MRI). Among these, CT imaging is considered the gold standard for lung cancer screening and diagnosis, particularly with the introduction of low-dose CT (LDCT) for high-risk populations. LDCT has demonstrated significant potential in reducing mortality by enabling earlier detection of small, potentially curable tumors.

In recent years, artificial intelligence (AI) and deep learning techniques have been increasingly integrated into imaging workflows to enhance the accuracy and efficiency of lung cancer diagnosis. Computer-aided diagnosis (CAD) systems are designed to assist radiologists by identifying potential malignancies, measuring tumor size, and tracking changes over time. These systems leverage large datasets of annotated medical images to train algorithms capable of detecting patterns that may be imperceptible to the human eye.

One of the primary challenges in using AI for lung cancer imaging is the limited availability of high-quality annotated datasets, which are critical for training robust machine learning models. Data augmentation techniques, such as affine transformations and generative models like Deep Convolutional Generative Adversarial Networks (DCGAN), are employed to address this limitation. These methods enhance the diversity and size of training datasets by generating synthetic images or applying transformations to existing data. By improving the variability of training datasets, data augmentation not only boosts model performance but also contributes to more reliable and generalizable diagnostic tools.

2 Materials ad methods

Dataset description

The dataset for lung cancer segmentation [23] consists of CT images paired with corresponding lung cancer masks, meticulously labeled by radiologists following the Lung-RADS System guidelines. This dataset combines two sources: original Kazakhstani data from the Kazakh Research Institute of Oncology and Radiology and re-labeled images from the publicly available LIDC-IDRI dataset [24]. The re-labeling process ensured consistency and adherence to the Lung-RADS classification system.

Data Preparation

The dataset is divided into two subsets:

- Training set: 708 CT images
- Testing set: 264 CT images

All images were standardized and formatted to include the following fields:

- label1: Class label according to the Lung-RADS System.
- mask: Binary mask identifying the lung cancer region.
- hu_array_old: The original CT image normalized to Hounsfield Units (HU).
- hu_array: CT image with non-lung areas removed via a thresholding-based algorithm.

Data Annotation

- label1 and mask fields: These fields were manually labeled by a board-certified radiologist to ensure clinical accuracy.

- hu_array field: This field was generated using an automated thresholding-based algorithm to isolate the lung regions from other anatomical structures. This process was not manually reviewed, which may introduce minor segmentation inaccuracies.

Preprocessing Pipeline

- Thresholding-based lung segmentation: Non-lung areas were excluded based on HU values, retaining only relevant regions for analysis. This step was applied to all images to create the hu_array field.
- Normalization: Pixel values of CT images were normalized to the range [0, 1] to enhance compatibility with the deep learning models.
- Contrast Enhancement: Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to the normalized images to improve contrast and facilitate better feature extraction during training.

DCGAN

Image generation, a cornerstone of advancements in computer vision, has emerged as a transformative tool in medical imaging. By leveraging machine learning models, particularly generative adversarial networks (GANs), researchers and clinicians can create realistic synthetic images to address the challenges of data scarcity and variability in medical datasets. These generated images mimic the characteristics of real medical scans, such as CT or MRI images, and are often used to augment datasets for training diagnostic models. This approach enhances the performance of deep learning algorithms by introducing additional variability and improving generalization. In the context of lung cancer, for instance, synthetic images of tumor regions can enrich training datasets, enabling models to better detect and segment malignancies, even in small or imbalanced datasets.

Advanced generative models such as Variational Autoencoders (VAEs), Deep Convolutional GANs (DCGANs), and StyleGANs are particularly effective for medical image generation. These models produce high-quality, high-resolution images that are almost indistinguishable from real scans. Beyond augmenting datasets, image generation techniques are also used for domain adaptation (e.g., translating CT images to MRI), denoising, and enhancing image quality. However, despite their benefits, these methods pose challenges such as high computational requirements, potential biases in generated data, and the need for clinical validation to ensure the synthetic images are accurate and clinically relevant. Addressing these challenges is critical to fully unlocking the potential of image generation in advancing medical imaging and improving patient outcome

Generative Adversarial Networks, first introduced by Goodfellow, comprise two neural networks - the generator and the discriminator – that compete in a zero-sum game. The generator aims to produce realistic images, while the discriminator attempts to distinguish between real and synthetic images. Through this adversarial process, GANs learn to generate high-fidelity images that are indistinguishable from real ones. This capability is particularly valuable in the medical field, where GANs can be leveraged to create synthetic images for rare diseases, enhance image resolution, and generate annotated training data for supervised learning tasks. The architecture of DCGAN is shown in Figure 1.

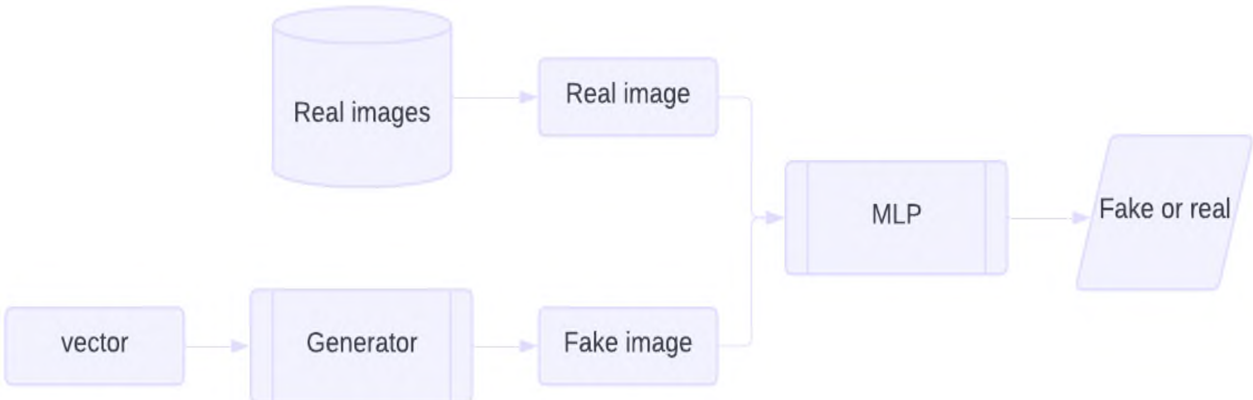

Figure 1 – DCGAN model architecture

U-Net model for image segmentation

Segmentation is a fundamental process in image analysis and computer vision, aimed at dividing an image into meaningful regions or objects. In medical imaging, segmentation involves identifying and isolating specific anatomical structures, tissues, or pathological regions, such as tumors or lesions, from medical scans like CT or MRI images. This process is critical for various applications, including diagnosis, treatment planning, and disease monitoring.

Segmentation can be broadly categorized into two types: semantic segmentation and instance segmentation. Semantic segmentation assigns a class label to each pixel in an image, ensuring that all pixels belonging to a specific class (e.g., "lung" or "tumor") are grouped together. Instance segmentation goes a step further by distinguishing between individual objects of the same class, such as multiple tumors within the same scan.

Achieving accurate segmentation is challenging due to factors such as noise, variability in anatomical structures, and the presence of overlapping or similar-looking regions. Advanced methods, including deep learning models like U-Net, leverage convolutional neural networks (CNNs) to automate and enhance the segmentation process, significantly improving efficiency and precision compared to manual approaches. Segmentation is a critical step in developing computer-aided diagnosis (CAD) systems, enabling clinicians to make informed decisions and improving patient outcomes.

U-Net [16] is a convolutional neural network architecture specifically designed for biomedical image segmentation. Introduced by Ronneberger et al. in 2015, U-Net has gained widespread adoption due to its ability to achieve high segmentation accuracy even on small datasets. The architecture consists of a symmetric encoder-decoder structure: the encoder (or contraction path) captures contextual information through a series of convolutional and max-pooling layers, while the decoder (or expansion path) restores spatial resolution via up-sampling and convolution operations. A distinctive feature of U-Net is its skip connections, which directly link corresponding layers in the encoder and decoder paths. These connections help retain spatial details and improve segmentation accuracy, particularly for small or irregularly shaped regions like lesions or tumors. U-Net is computationally efficient and performs well even in cases of class imbalance, making it an ideal choice for tasks such as lung cancer segmentation in CT images. U-Net model architecture is shown in Figure 2.

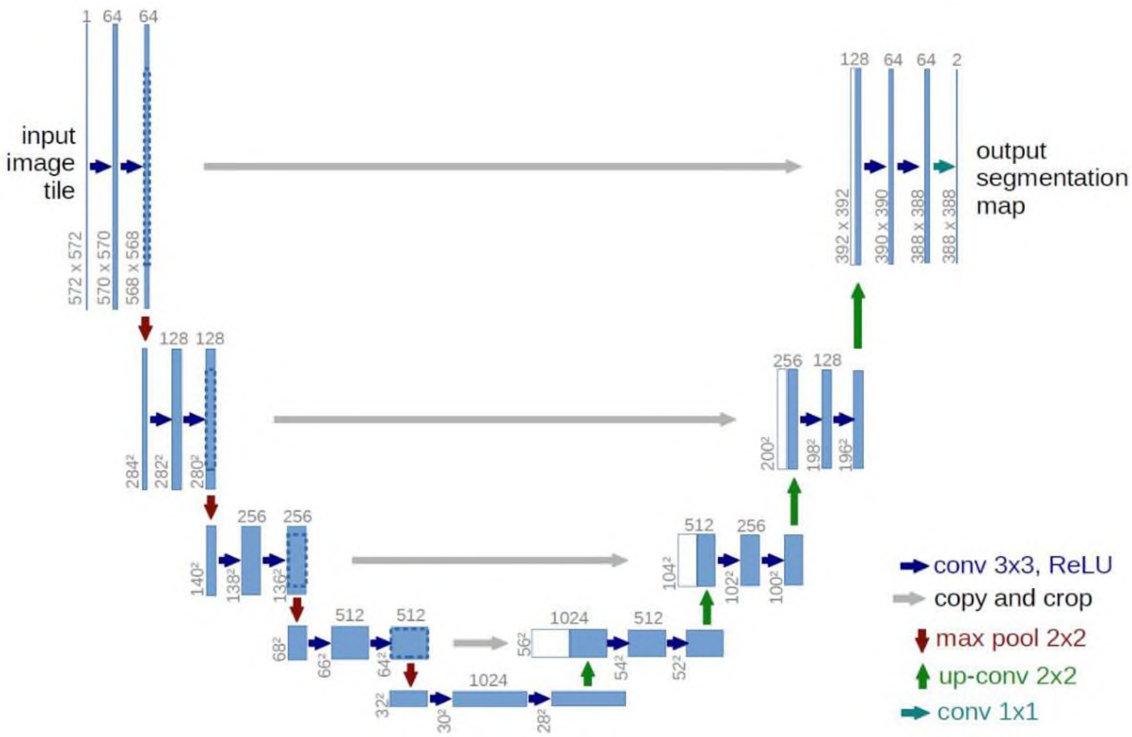

Figure 2 – U-Net model architecture

3 Results

The application of the Deep Convolutional Generative Adversarial Network (DCGAN) significantly improved the segmentation performance for lung cancer on CT images. Using the DICE similarity coefficient as the evaluation metric, the baseline model without data augmentation achieved a score of 0.3708. After incorporating synthetic data generated by DCGAN, the DICE score improved to 0.4191, indicating a substantial enhancement in the segmentation quality.

This improvement highlights the effectiveness of DCGAN in generating realistic synthetic images that enhance the training dataset's diversity and variability. The ability to produce high-quality augmented data demonstrates the potential of DCGAN to address the challenges of limited datasets in medical imaging, contributing to more accurate and reliable segmentation outcomes.

4 Discussion

The application of Deep Convolutional Generative Adversarial Networks (DCGAN) in lung cancer segmentation demonstrates promising results, as evidenced by the significant improvement in the DICE similarity coefficient from 0.3708 (baseline) to 0.4191. This enhancement underscores the capability of DCGAN to generate realistic and diverse synthetic data, effectively enriching the training dataset and improving the model's segmentation accuracy. The use of DCGAN is particularly advantageous in scenarios where obtaining large, annotated medical datasets is challenging due to privacy concerns, resource limitations, or the labor-intensive nature of manual labeling.

However, the implementation of DCGAN comes with notable challenges. The model's high computational complexity and resource demands can be a limiting factor, particularly in resource-constrained environments such as smaller medical institutions or regions with limited access to advanced hardware. Training DCGAN requires significant computational power, including high-performance GPUs and extended training times, which may not always be feasible. Furthermore, the optimization of GAN models can be unstable, often requiring careful tuning of hyperparameters and monitoring to prevent issues such as mode collapse.

Despite these challenges, the benefits of DCGAN, including its ability to generate diverse and clinically relevant synthetic data, make it a valuable tool in medical image processing. Future research should focus on developing more computationally efficient variants of GAN architectures or hybrid approaches that combine the strengths of traditional augmentation techniques with advanced generative models. Additionally, exploring methods to reduce the reliance on extensive computational resources without compromising the quality of synthetic data could further enhance the practicality and accessibility of DCGAN-based solutions in medical imaging.

5 Conclusions

The application of Deep Convolutional Generative Adversarial Networks (DCGAN) in lung cancer segmentation has demonstrated its potential to significantly enhance segmentation accuracy through the generation of realistic and diverse synthetic datasets. By improving the DICE similarity coefficient from 0.3708 to 0.4191, DCGAN has proven its ability to address challenges associated with limited and imbalanced medical datasets, offering a practical solution for enriching training data. This advancement underscores the transformative role of generative models in medical image analysis and their capability to support the development of more accurate and reliable diagnostic tools.

However, the challenges associated with DCGAN, such as high computational complexity and resource demands, highlight the need for further research into optimizing these models for resource-constrained environments. Future efforts should prioritize developing more efficient architectures, hybrid augmentation techniques, and strategies to reduce dependency on high-performance hardware. Additionally, ensuring the clinical relevance of synthetic data and addressing stability issues in model training remain critical areas for improvement.

Overall, while DCGAN presents certain limitations, its advantages in generating high-quality synthetic medical data make it a valuable tool in advancing lung cancer imaging and segmentation. Continued exploration of generative models and their applications in medical imaging holds great promise for improving early diagnosis and treatment outcomes, ultimately benefiting patients and healthcare systems alike.

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НАМ, Д.

ГЕНЕРАТИВТІ АДВЕРСАРЛЫҚ ЖЕЛІЛЕРДІ (GAN) ӨКПЕ ОБЫРЫНЫҢ КТ СУРЕТТЕРІН ГЕНЕРАЦИЯЛАУ ҮШІН ҚОЛДАНУ

Өкпе обыры онкологиялық аурулардан болатын өлімнің басты себептерінің бірі болып қала береді, бұл ерте диагностика мен диагностикалық құралдарды жетілдіруді қажет етеді. Бұл зерттеуде өкпе обырын сегментациялау үшін КТ кескіндері деректерін арттыру мақсатында DCGAN (терең конволюциялық генеративті адверсарлы желілер) қолдану зерттелді. Қазақстандық жергілікті деректер мен қайта өңделген LIDC-IDRI жинағының үйлесімі пайдаланылып, DCGAN шынайы синтетикалық кескіндерді жасап, сегментация сапасын жақсартты. DICE метрикасы бойынша бағаланған U-Net моделі дәлдікті 0,3708-ден 0,4191-ге дейін арттырды. DCGAN-ның әлеуеті жоғары болғанымен, оның есептеу ресурстарына деген жоғары талаптары маңызды мәселе болып қала береді.

Түйінді сөздер: *DCGAN, өкпе ісігі сегментациясы, кескінді өңдеу, компьютерлік көру.*

НАМ, Д.

ПРИМЕНЕНИЕ МОДЕЛЕЙ ГАНОВ ДЛЯ ГЕНЕРАЦИИ КТ СНИМКОВ РАКА ЛЕГКОГО

Рак лёгкого остаётся одной из ведущих причин смертности от онкологических заболеваний, что требует улучшения методов ранней диагностики и инструментов для диагностики. В данном исследовании изучено применение глубоких сверточных генеративных состязательных сетей (DCGAN) для увеличения объёмов данных КТ изображений для сегментации рака лёгкого. Используя комбинацию данных из Казахстана и переработанного набора LIDC-IDRI, DCGAN создавал реалистичные синтетические изображения, улучшая качество сегментации. Модель U-Net, оцененная по метрике DICE, продемонстрировала повышение точности с 0,3708 до 0,4191. Несмотря на перспективы использования DCGAN, его высокие вычислительные затраты остаются серьёзным вызовом.

Ключевые слова: *DCGAN, сегментация рака легких, обработка изображений, компьютерное зрение.*

Information about author:

Nam Diana *– PhD Student, senior lecturer, Kazakh British Technical University, Almaty, Republic of Kazakhstan.*

Нам Диана *– докторант, аға оқытушы, Қазақстан-Британ техникалық университеті, Алматы қ., Қазақстан Республикасы.*

Нам Диана *– докторант, старший преподаватель, Казахстанско-Британский технический университет, г. Алматы, Республика Казахстан.*

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ГУМАНИТАРЛЫҚ ЖӘНЕ ӨНЕР ҒЫЛЫМДАРЫ

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Компьютерлік беттеу: *С. Красикова*

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Корректоры: *Б. Сыздыкова, Т. Цай*
Компьютерная верстка: *С. Красикова*

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